# POWER PERFORMANCE ASSESSMENT OF BUILDING ENERGY SYSTEMS

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Architecture

Georgia Institute of Technology
August 2016

**POWER PERFORMANCE ASSESSMENT OF BUILDING ENERGY SYSTEMS**

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to my family

# ACKNOWLEDGEMENTS

This work would not have been possible without the opportunity provided by my advisor, Prof. Augenbroe. I cannot thank him enough for his support, patience, and guidance. I am thankful for all his efforts in transferring knowledge in terms of both domain specific topics and research methodology. I truly respect and admire him not just because of the insightful scholar, visionary researcher, inspirational advisor, and brilliant teacher he is but also because of the great human being he has attained to be. Thanks for caring to make “the life of every living thing nobler and more beautiful.”

I would like to thank my family for all their love and encouragement; I could not have accomplished this work without their support. My siblings and I would not have been where we are today without the values and principles learned from our parents throughout our life. I am thankful for having my sister, Raheleh, my best cousin, Nazanin, and my brothers, Babak and Amir Ali who have been my lifetime best friends and supporters regardless of my shortcomings or achievements.

My time at GA Tech was made enjoyable in large part because of colleagues and friends in the Building Technology Program who became a part of my life. They have been not only great companies to work with but also good friends to enjoy our free time with. Many thanks to Yeonsook, Roya, Huafen, Paola, Sanghoon, Fei, Zhengwei, Jihyun, Yuming, Qimpug, and Qi. Also, I must thank all other friends in the PhD program especially: Sherif, Hui, Hugo, Paula, Marcelo, Anna, Miklos, Kereshmeh and many others who made this PhD journey even more interesting and unforgettable.

I would also like to give my special thanks to my colleagues, friends, and managers at Pacific Northwest National Laboratory for being supportive, understanding, engaging, and motivating during the years I tried to have a full time job while working on my dissertation. Many thanks to Viraj, Vrushali, Rahul, Supriya and others whom collectively made my life in Richland, WA comfortable, memorable, and exciting. I should also thank all my other friends in Tri-Cities. I am grateful to Linda and Stanley for their unconditional friendship and endless kindness. With them and in their house, I always found peace and stability during all those uncertain days.

I am indebted to my long-time mentor, Mr. Bagheri for teaching me wisdom and philosophy of happy living. I am not sure if anyone else would have become as happy and proud of me for getting a PhD as much as he always expressed he would be.

Last but not least, I am grateful to my loving, supportive, inspiring, and patient fiancé, Mohsen that I met during the PhD journey. This dissertation would not have been finished without his continuous encouragement, support and optimism.

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# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| AHU | Air Handling Unit |
| CBECS | Commercial Buildings Energy Consumption Survey |
| CVR | Conservation Voltage Reduction |
| DCV | Demand Control Ventilation |
| DER | Distributed Energy Resources |
| DG | Distributed Generation |
| DR | Demand Response |
| DRQAT | Demand Response Quick Assessment Tool |
| DSM | Demand Side Management |
| EEM | Energy Efficiency Measure |
| EIA | Energy Information Administration |
| EPA | Environmental Protection Agency |
| EPBD | Energy Performance of Buildings Directive |
| HVAC | Heating, Ventilation, and Air Conditioning |
| IEQ | Indoor Environmental Quality |
| ISO | Independent System Operators |
| kW | Kilowatt |
| kWh | Kilowatt Hour |
| MPC | Model Predictive Control |
| OA | Outdoor Air |
| OpenADR | Open Automated Demand Response |
| PI | Performance Indicator |
| RTU | Rooftop Unit |

# SUMMARY

Buildings are the main consumers of electricity across the world. In the past research, the focus has been on evaluating the energy performance of buildings whereas the instantaneous power consumption of systems and aggregated load profiles have received less attention. Today, buildings are involved in the challenges of 'power grid modernization.' This is mostly because the increasing diversity of building systems requires a better understanding of their behavior during peak hours and the "demand charges" that are associated with it. Other drivers are the need to lower the carbon footprint of the electricity supply (i.e., reduction of grid as well as building scale emissions) and the growing number of demand response (DR) programs that rely on dynamic adjustments of building systems to support grid stability and resiliency. However, we lack methods, models, and performance measures that support building-grid interaction evaluations. This thesis has developed methods and models needed to study and assess performance of buildings in the electricity system. To achieve this, building thermal models, conventionally used to capture energy consumption are enhanced with electricity characteristics (e.g., voltage). With these models the impact of voltage on load shape of different systems is investigated and a set of quantitative power performance indicators (PIs) defined. These PIs are consequently applied to a variety of building control strategies in the context of DR scenarios. The developed PIs provide the fundamental component needed in decision support and auto-DR systems to quantitatively, systematically, and consistently compare and assess power performance of different building system types in given operation scenarios. This assessment is important for a range of applications. At

building level, facility managers can use quantitative performance comparison of control strategies for both energy efficiency and peak reduction decisions. At grid level, our method can be used for power planning and management studies such as load forecasting.

In the first part, this thesis demonstrates the feasibility of the thermal enhanced models with electrical characteristics by developing these models and showing how they can be constructed and used for different system types. In the second part, this thesis verifies usability of the performance assessment framework developed for DR and energy management decisions at building level. This is achieved by applying performance indicators defined to a set of scenarios. Results indicate how each performance indicator can support different performance criteria such as power and energy efficiency while maintaining thermal comfort of occupants. These quantitative PIs can be implemented in decision support systems that consider the trade-off between energy efficiency and investments in power management at the building site.

# 1. INTRODUCTION

## 1.1 Background and Motivation

Electricity production is the leading source of greenhouse gas emissions in the U.S. (EPA, 2013). It is responsible for 31% of greenhouse gas emissions in 2012 followed by transportation (27% in 2012), industry (21%), commercial and residential buildings (12%), and agricultural (9%) sector (EPA, 2013). According to recent statistics published by the U.S. Energy Information Administration (EIA), buildings are the main consumers of electricity (EIA, 2012). In 2011, residential and commercial building sectors used 38% and 36% of electricity sold in the United States respectively (Figure 1.1). Buildings are the main consumers of electricity with a variety of system types and different load profile. This introduces variations in power flow contributing to instability and unreliability in the power system. Therefore, understanding buildings' electricity demand play an important role in planning and management of the power grid especially in the emerging modern grid with 'smart' features.

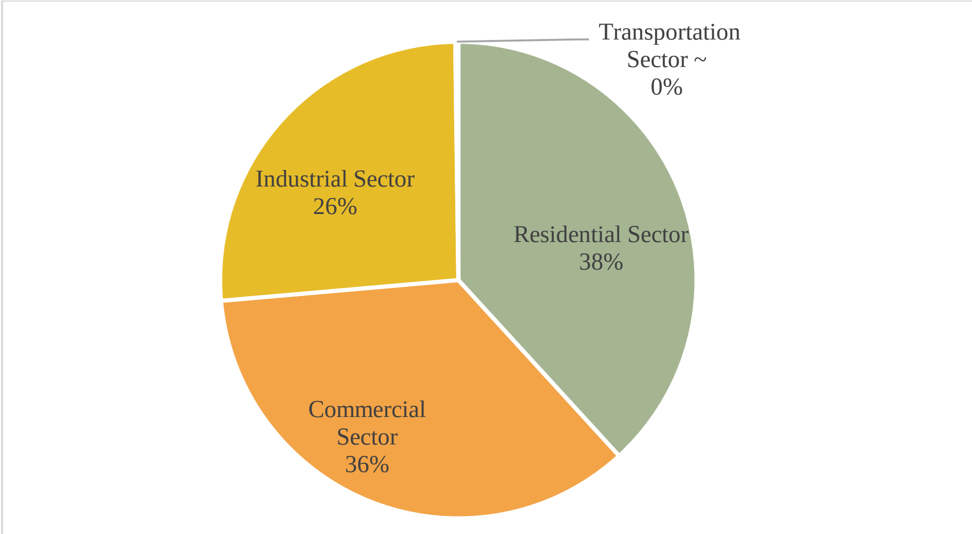


Figure 1.1 2011 Electricity Retail Sales in the U.S. (EIA, 2012)

Many energy related topics and studies including the use of buildings as energy assets began to shape during energy crisis of the 1970's. Work related to the use of buildings to support power system objectives (e.g., stability, sustainability, and resiliency) such as demand side management (DSM) is among those which started in the 1980's (Gellings, 1985). DSM introduced different methods such as peak clipping, valley filling, load shifting, flexible load shape, and energy conservation as strategies to reduce power use during peak load hours. These strategies are applied at building level. Demand response (DR) programs are launched to achieve DSM and control load to reduce peak demand. DR programs and mechanisms have been growing in number and type. Power utilities and aggregators are offering different types of DR mechanisms such as direct load control (DLC), price-based, and transactive-control or market-based control (Kosek, 2013)[1] to residential and commercial buildings across the U.S.

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[1] DR mechanisms will be further discussed in the following chapters.

Commercial building electricity demands are mostly schedule-driven with less variation in load during the day when compared to residential buildings. Yet, they have a big contribution to summer peak demand (Koomey, 2002). The concern about peak demand and variations in load have resulted in an increase in the research and development (R&D) of impact assessment of HVAC systems on performance of the power grid system. Tomiyama et al. (1998), Hood (2004), Kiliccote et al. (2006a), Lin et al. (2013), and MacDonald et al. (2014) are examples of such studies. Hence, methods and strategies related to integration and interactions of buildings with the power grid have been growing in number and complexity. This thesis also belongs to the pool of studies related to building integration in the power grid and is concerned with a systematic and quantitative approach for power performance assessment of building systems in the power grid and models needed to support related analysis.

## 1.2 Demand Side Management

Historically, the goal of the electric power grid has been to balance the supply and demand and deliver electricity to consumers in a cost-effective and reliable way. The energy crisis of the 1970's raised the need for a sustainable energy system and sustainability became a new objective for the electricity system, which is one of the largest energy systems in the world. Today, the increasing diversity and variability of loads and the growing penetration of intermittent renewable generation sources have introduced more volatility to the power system requiring the power grid to be able to absorb such variations without disruptions. This cannot be achieved without new mechanisms and techniques considered at building level commonly known as demand side management (DSM) techniques. These techniques include energy efficiency and conservation, peak load management and demand response (DR). Kiliccote et al. (2006b) specified the motivations, design, and operation of these strategies as summarized in Table 1.1. Deployment of these techniques enhance power management in order to achieve a more stable, reliable, and resilient power grid.

Table 1.1 DSM terminologies as defined by Kiliccote et al. (2006b).

| | Efficiency and Conservation | Peak Load Management | Demand Response |
|---|---|---|---|
| Motivation | Sustainability, economic and environmental benefits | Economic savings and grid peak reduction | Economic Reliability |
| Design | Energy efficient buildings | Low power design systems | Dynamic control capacity |
| Operations | Integrated system operations | Demand limiting and demand shifting | Demand shedding, shifting, and limiting |
| Initiation | Local | Local | Central |

Substantial efforts in the area of building energy efficiency and conservation methods have been going on to achieve energy efficiency goals defined by the government (e.g., 20% energy reduction by 2020). Energy conservation has been achieved by applying different energy efficiency measures (EEMs) e.g., energy efficient envelope, lighting, and HVAC in the design or during operation of a building. Although EEMs can permanently reduce peak demand by reducing overall consumption (Figure 1.2), there are limited studies (if any) that show and prove reduction in the ratio of peak-to-average load as a result of EEMs. In fact, EIA data show an increase in the ratio of peak-to-average load ratio in the past decade (EIA, 2014). The cause of this has remained unknown, but there are potential causes. For instance, we know for sure that during this timeline, buildings adopted more EEMs, the diversity in system types (e.g., heat pumps) increased, and more renewable and distributed generations (DGs) became part of the electricity system. Data also shows an increase in demand charges in different states indicating an increase in peak to average demand ratio. These could imply that efficiency and conservation methods do not necessarily result in peak reduction. Yet, energy efficiency can be integrated with other DSM methods and mechanisms to achieve optimum results in terms of both energy efficiency and peak reduction (i.e., power efficiency).

Peak load management refers to strategies conducted at building level by facility managers to reduce demand charges and higher energy rates e.g., time-of-use (TOU) pricing during peak hours. Methods used for peak load management include load clipping (i.e., demand limiting) and demand shifting. Load clipping or shaving methods (Figure 1.2) intend to clip or cut the peak resulting in net energy reduction in addition to less demand charges. Demand shifting (Figure 1.2) does not necessarily result in net energy savings because they only change the time that electricity is used and intend to shift load to hours with lower demand and consumption charges by taking advantage of the thermal energy storage in buildings e.g., through nightly or early morning pre-cooling.

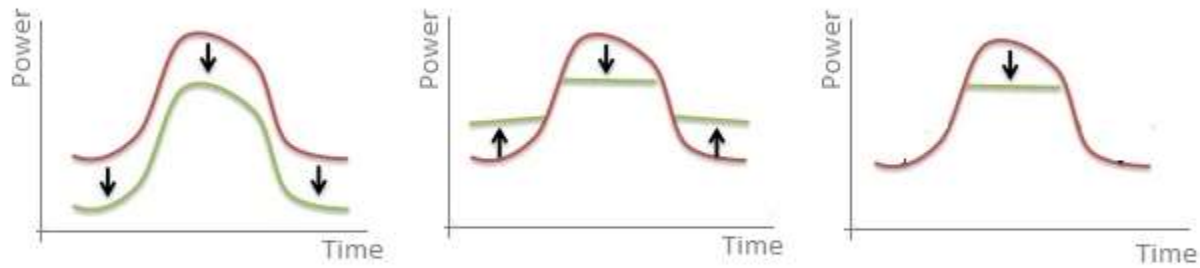


Figure 1.2 Three common methods of DSM (left: energy conservation, middle: shifting load, and right: clipping or cutting load)

Demand response (DR) is defined as intentional modifications in electricity usage of end-use customers from their normal consumption patterns (in terms of both timing and magnitude) in response to “changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” (DOE, 2006). DR has been considered as a promising technique. This is because there are about 5.6 million commercial buildings in the U.S., comprising 87.4 billion square feet of floor space, consuming 36 % of electricity generated, and contributing to 1/3 of peak demand (DOE 2006; EERE, 2011; EIA, 2012). The large amount of power consumed by buildings, variations in consumption and load type, and enormous thermal storage capability of commercial buildings make them a great resource for DR (Oldewurtel et al., 2011; Hao et al., 2014; Hughes et al., 2015; and Wang et al., 2014). DR mechanisms are discussed in more detail in the following section.

## 1.3 Demand Response Mechanisms

DR strategies can be generally classified into three types: 1) price-based or indirect control, 2) market-based or transactional control, and 3) direct load control (DLC). Figure

1.3 shows a classification summary for DR control strategies in terms of communication direction and location of decision making in terms of responding to a DR signal.

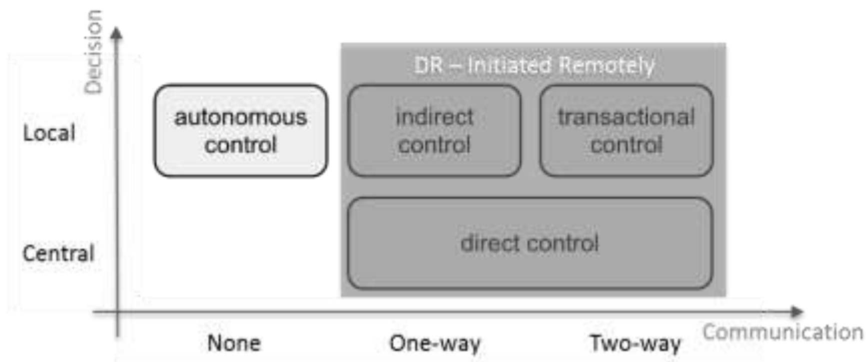


Figure 1.3 Classification of DSM and DR (Source: based on Kosek, et al., 2013)

Price-based DR is an indirect control strategy relying on customers changing their electricity consumption in response to a signal (most commonly a price signal). In this method, the energy consuming system receives the signal but may or may not respond to the signal or send any feedback. There are two characteristics of the indirect control: 1) “indirectness of the relationship between control objective and observables”, and 2) “local and independent decision making of the DER makes its behavior non-deterministic” (Heussen et al., 2012). These time-varying pricing mechanisms include time-of-use, critical peak, and real-time pricings (Li et al., 2011). Price-based DR strategy is simple and easy to deploy. However, the quantity and quality of DR is unpredictable because the consumer has no obligation to respond to the signal making price-based DR unreliable. Therefore, applying real-time pricing scheme in large scale will result in volatility and instability of the power system (NERC, 2007).

Market-based control is another DR mechanism, which is considered as a distributed control strategy. This method, which is also referred to as ‘transactive’ energy control, uses market mechanisms (e.g., bidding) to engage self-interested responsive loads to provide services to the grid. According to The GridWise Architecture Council, “transactive energy refers to the use of a combination of economic triggers and control techniques to improve grid reliability and efficiency.” (GridWise, 2015). In this strategy, the only information needed to be exchanged between the electric loads and system operator are the price and quantity of intended electricity consumption. Hence, one of its major benefits is that it respects customers’ privacy, preference, and freewill. PowerMatcher is an example of market-based on transactional control scheme (Bliek et al., 2010).

DLC involves direct DR communication with the building and its systems and allows utilities, Independent System Operators (ISO), or aggregators to remotely control (e.g., turn on and off) specific building electric systems or appliances during peak demand hours or critical hours (Koch & Piette, 2009; Kosek et al., 2013). DLC may use a one-way or two-way communication scheme to interact with the controlled device (i.e., distributed electricity end users). In the one-way communication, the building has no further control and is obliged to respond to the DR signal. However, in the two-way communication, the building is supposed to first acknowledge that it has received the signal and should update the systems of the current DR status, but it can decide how to control its systems in order to respond to the DR signal. The two-way communication schema is also referred to as facility-centric load control (FCLC) (Koch & Piette, 2009). This strategy provides more flexibility to manage energy in buildings and allows facility managers to choose control strategies that best fit their requirements. This is more ideal for large commercial buildings with more advanced building automation systems (BAS). AutoDR is an example of the two-way communication DLC strategy supported by OpenADR (OpenADR, 2015; DRRC, 2015; Koch & Piette, 2009), which is tested in different studies (Kim et al., 2013 and Yin et al., 2010) and implemented by utilities such as SDG&E, PG&E, and Con Edison.

DLC strategies and its variations have mostly been used for DSM to reduce peak e.g., peak clipping, valley filling, load shifting, flexible load shape, and energy conservation. The main advantage of DLC compared to indirect strategies (e.g., price-based or market-based control) is that the operator has more certainty about the amount of load being shifted. However, DLC "involves direct communication with individual appliances, and detailed information on their interactions with the surrounding environment. This is more computationally and transaction intensive, but allows a more precise response and individual control setpoints can be sent to each appliance, facilitating control of demand response at the highest possible geographic resolution" (O'Connell et al., 2014).

Selection of the right DR mechanism is application based and depends on the nature and requirements of the services provided. For instance, for an ancillary service that is at a time resolution shorter than five minutes (e.g., frequency regulation), DLC is recommended to be a more appropriate strategy to ensure the reliability and certainty of the program (Callaway & Hiskens, 2011; O'Connell et al., 2014; Somasundaram et al., 2014). Market-based mechanisms are more suitable for ancillary services that are at time scales from minutes to hours. Price-based DR strategies would be sufficient for planning and ancillary services that are at larger time scales (from months to years).

Reducing the cost of electricity in buildings requires close attention to the structures of electricity tariffs, which consider the time and the quantity of electricity used. Electricity pricing structures can be complex, including time-of-use, demand, peak-demand, and other charges. Some recent DR programs and tariffs that utilities or independent system operators (ISO) offer provide larger incentives if more sophisticated building operational and control strategies are considered that reduce electricity use during occasional events. Regardless of DR type and application, it is important to study performance of DR under different scenarios and we argue that DR performance should in fact be assessed at building level for design and operation purposes.

The number of DR studies have increased in the past years, however, most of them have focused on residential buildings and DR performance at the large scale (i.e., feeder level up) such as Koomey et al., 2002; Kiliccote et al., 2006a; Hammerstrom et al., 2007; Coughlin et al., 2008; Cui et al., 2014; and DRRC, 2015. Studies related to the impact of DR strategies at the building level in commercial buildings, e.g., Yin et al. (2010), are limited both in terms of number and details of their assessment. In case of DR evaluation by Yin et al. (2014), the only measurement considered for DR evaluation was the magnitude of power [KW] savings at different setpoint levels. Models used to estimate and predict energy and power savings in presence of DR strategies are either data-driven e.g., Coughlin et al. (2008) or physics-based such as DRQAT (Demand Response Quick Assessment Tool), which is based on the EnergyPlus modeling and simulation engine (Xu, P. and Yin, R., 2009). There are also a number of field studies that have implemented different control strategies in commercial buildings to capture their impact on load profile (e.g., ISO New England, 2003; Piette et al., 2004; CEC, 2006; Kiliccote & Piette, 2008; Motegi et al., 2007; Kim, et al., 2013). However, none of these studies has carefully and successfully quantified and assessed performance of these strategies in detail using a set of performance criteria, especially from the perspective of the building, i.e., the ‘response’ side. The challenge is to introduce of a set of objective performance criteria with which different solutions could be ranked against each other.

## 1.4 Importance of Building Power Modeling

The power grid we are still using today was engineered during an era when energy was cheap, environmental issues were not a priority, consumers were not active decision-makers in the power system, types of loads were limited, and there were no on-site renewable energy and distributed power generation systems. Aggregated load models were sufficient for power (i.e., load) flow analysis to support delivery of reliable and inexpensive power to end-use consumers. As a result, load management and forecasting were not as challenging as they would be in presence of a modern and smart grid. However, with all the upgrades and changes the grid is undergoing, more suitable load models are also in demand. These models should: 1) support different building energy systems and their control strategies and 2) be able to capture electrical characteristics of different load types. These are needed to support different mechanisms and elements of the modernized power grid e.g., DR or other grid-based control strategies such as CVR. In addition to that, constructing such models and methods are necessary to successfully quantify power performance of building energy systems especially for studies related to electrical-based control strategies.

## 1.5 Importance of Building Power Performance Assessment

Being able to quantify power performance of buildings will support facility managers, building owners, researchers, and engineers to understand the underlying mechanisms, interactions, and elements that affect power performance of building energy systems in the power grid with application to DSM and DR. The significance of assessing power performance of buildings in the power grid can be revealed in its applications in different spatial and temporal scales of decision making from building level all the way to the grid interconnection level. Performance quantification is the underlying component in any decision analysis tool needed for facility management and power planning and management to quantify the trade-off between two alternatives.

## 1.6 Gaps in Knowledge

One of the modern areas in applied science which has made significant advances in the last decades is building performance modeling and simulation. Representation of building geometry, materials, and systems using physics-based models have become sophisticated and more widely used. This is owed to higher demand and need for energy efficiency, which requires better understanding and assessment of building energy performance and also due to advancements in computational resources. In comparison, however, there is a lack of methods and models for representing power performance of buildings in the building simulation practice. This implies the necessity of sustained research and development efforts concerning mechanisms including methods, models, and metrics that describe the power performance of buildings as major components of the power system, known as load.

Adding 'digital intelligence' to the power grid by using sensors, meters, digital controls and analytic tools will facilitate automation, monitoring, and control of two-way energy flow in the power system. However, we do not have a good understanding of the impact of such technologies and how they translate into building energy and power efficiency measures. Studies and research in this area are limited partly because buildings are not modeled in detail in the current power modeling and simulation tools (Mota & Mota, 2004; Singh & Mistra, 2007; Singh & Mistra, 2012; Exarchakos et al., 2009; Vytelingum et al., 2010; and Beradino & Nwankpa, 2010). In the current power system studies, buildings are treated as single node loads and constructed in an ad-hoc manner; i.e., in some cases a building is assumed to be a black box of constant power load model (Concordia and Ihar, 1982; Price et al., 1988; Ranade et al., 2001; Choi et al., 2006).

It has been long recognized and well known that load characteristics have a significant impact on performance of the power system and the results of load flow[1], voltage, and transient stability simulations are known to be highly dependent on the assumptions undertaken for load models and their parameters (Concordia and Ihar, 1982; Price et al., 1988; Kundur, 1994; IEEE, 1995; Stojanovic et al., 2008). In the power system, the generation, transmission, and distribution of power as well as its storage and demand are all codependent. Power supply must continuously match demand in addition to the losses on the grid. The supply and demand balance on the grid should be maintained from moment to moment to avoid outages and damage to the equipment connected to it. To achieve this,

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[1]Load flow analysis in power studies is determination of the steady state voltages at each node in the power grid under a certain set of generation and loading conditions

load is forecasted at different temporal scales to minimize interruptions and ensure power quality delivered to end-users. To forecast and manage load, different load modeling methods are used by utilities for power management and planning, however these models are not sophisticated enough to support the future needs of the power grid.

A survey related to current power industry practice was conducted back in the late 1980's and its result showed that most industry representatives in North America who responded to the survey did not use any load modeling approach/software and 50% of those who did use some form of load modeling were not satisfied with their load models and were pursuing work to improve them by gathering more detailed end-use data to develop new models or validate existing ones (IEEE, 1993). Most relevant studies in this area are only concerned with the power flow up to the point it reaches buildings and the effects of buildings have been underestimated. Building-grid interactions are bi-directional and therefore the lack of such detailed building thermal models in the power system means we also do not well understand the impact of building energy and power performance on the power system and vice versa. In other words, the integration and coupling of electrical and thermal characteristics of buildings is not adequately captured using existing models although there is research related to significance of load models in power system simulation (Ranade et. al., 2001; Choi et al., 2006; and, Singh, 2007;).

More recent literature and research in this area expresses even more concern about the lack of detailed load models. As the need to upgrade the power system increases, it becomes more critical to have a better understanding of buildings and their energy consumers in the power system. Hence, more accurate load models are required to capture the performance and behavior of building energy systems (e.g., HVAC) in the power grid in presence of stability issues caused by new system (i.e., load) types, their control strategies, building energy efficiency measures and other conservation methods such as renewables and DG (Cardell and Ilic, 2004), power factor[1] improvement, or conservation voltage reduction (CVR)[2] (Diaz-Aguilo et al., 2013).

Lack of detailed building energy and power models in the power system introduces limitations to both grid and building related studies and assessments. On the power grid side, lack of detailed load models introduces more uncertainty to the electric load prediction, control of the power flow, and our understanding of impact of grid-based control of building energy systems in the modern power grid, which is supposed to dynamically respond to load and demand (Gallego, 2012). On the building side, it takes away the opportunity to understand what new smart grid technologies (e.g., DR) mean in terms of building energy performance and how much energy can be saved through deployment of such mechanisms. For instance, current building modeling and simulation tools do not model interdependency of thermal and electrical flows in buildings in a manner that can offer beneficial and effective support to the control of power distribution (Kelly, 1998). This is because they are thermal-based models without electrical characteristics and hence cannot be used in moment to moment power flow models used in the electricity system for power studies. For building models to be integrated in the modeling and

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[1] Power factor is the ratio of real power to the apparent power or the cosine of the phase angle between current and voltage. A power factor of 1.0 means maximum load efficiency.
[2] CVR is a method to reduce energy consumption by reducing voltage.

simulation of the smart grid to achieve capabilities such as DR and multi-decadal planning, they should be able to inform us about load performance and electrical characteristics.

Impact of energy interventions on new and existing buildings should be considered in the context of power planning and load forecasting. Potential consequences of retrofitting, penetration of DGs, and other energy efficiency measures should be taken into account. Key factors that have large future uncertainties must be identified and potential consequences of these should be studied and projected. This will enable making informed decisions about investment, allocation of power and energy, and policy making in a risk-conscious way. The improvements required and challenges involved with modernization of the power grid justifies the need for a more reliable method of modeling load and subsequently power flows within building systems and the interaction between building stocks and the grid.

Integration of building thermal models with electrical models for load flow modeling within power distribution simulation engines will lead to improved control of power flow in the next generation of the power grid. The increased granularity will provide more opportunities and will be observed from different perspectives and several stakeholders. This will benefit utilities by improving power reliability and stability because it would enable more accurate prediction of faults in the system. Customers will also be able to take advantage of demand response programs that allow them to control and dispatch their own buildings loads. The coupling of the electric demand of building energy systems with the thermal response of the building will support better realization of the dynamic response of building system’s loads (Berardino et al., 2010; Kosterev et al., 2008; Schneider & Fuller, 2010). This will also benefit integration of emerging distributed generation such as renewable and alternative energy technologies.

In summary, there are two major drivers for selection of the subject of this thesis. The first is the lack of adequate and robust power performance quantification methods that can successfully measure the performance of a system, strategy, or mechanism against another one. The second is the lack of voltage dependent building energy and power models (i.e., load flow models) that can be utilized to capture a wider range of power reduction methods such as CVR and also to be utilized in more detailed power flow calculations to support requirements of power system studies. Such performance quantitation methods and power models are needed for different purposes: 1) to study and understand emerging technologies and promised capabilities of the modern grid at building scale, and 2) to be utilized in decision support systems at different temporal and spatial scales from building level for facility management to the grid level for power planning.

## 1.7 Research Questions and Hypothesis

This work is driven by three major hypotheses.

- Hypothesis 1: Complete energy and power performance assessment of buildings and their energy systems in the power grid cannot be realized without models that capture both thermal and electrical characteristics (e.g., voltage) of building systems.
- Hypothesis 2: Current building energy modeling and simulation tools are inadequate to study electrical characteristics of building energy systems needed for power flow and power assessment studies. On the other hand, power system

modeling and simulation tools do not capture detailed description of thermal behavior of buildings and energy systems[1]. Emerging technologies of the smart grid require better understanding of the dynamic behavior of buildings and energy systems in the power system. This cannot be achieved without adequate load models that support both thermal and electrical description of building and its energy consumers.

Hypothesis 3: We lack standards and methods including quantifiable performance indicators to measure, assess and compare performance of buildings in terms of load and power consumption in the electricity system.

These hypotheses will be tested through evaluation of the following use-cases:

1) Impact of different building system types on power consumption and load shape.
2) Power performance assessment of building energy systems using HVAC control strategies in presence of grid-based DR mechanisms.

These hypotheses should answer the following research questions:

1. In what ways and by what means can building science studies support power system studies such as electricity forecasting and power planning decisions?

[1] Single-zone building models have been implemented in an open-source power systems and simulation environment (i.e. GridLAB-D), but they do not capture characteristics of a multi-zone building. In addition to that, more complex heating and cooling systems used in commercial buildings (e.g. chillers) have also not been well understood in power modeling and simulation tools.

2. What is the impact of grid-based building energy management systems or control strategies on performance of our buildings? Or more specifically: can a set of performance indicators be defined that are useful for comparing and rating competing solutions in an objective and generic way. The importance of the latter cannot be understated. Whereas normalized energy (consumption) performance benchmarks (or reference PI) have been well established (e.g. kWh/m$^2$/year per given building functional equivalence class, defined by a normative scenario of usage, and per climate zone) this is not the case for power performance. On the contrary, there is no clear understanding of equivalence (i.e. what should be used as the basis for this?), nor is there a clear understanding of which scenarios of use, both in terms of endogenous scenarios such as system operation or as exogenous scenarios such as weather and grid operation dynamics, should be chosen to arrive at an objective PI-based comparison of different solutions.
3. How can building and facility managers make more informed decision about selection of an intervening HVAC control strategy to support energy and power management of buildings in presence of DR events?

## 1.8 Research Objectives

The primary objectives of this research are then defined as:

1) Extending thermal models of buildings with electrical characteristics to:
    a. Develop grid-ready detailed building energy models that can be integrated into power distribution simulation tools to support making more informed decisions about short-term power management and long-term power

planning. The thermal component of these models enhances studies such as consideration of building energy efficiency methods and retrofits in long term planning and load forecasting. The electrical component improved by thermal response of buildings supports shorter time and smaller scale power management decisions such as finding the right grid-based control strategy for each region. These models can also be used to quantify the impact of voltage variations on building energy consumption.

   b. Enhance building performance assessment studies related to implementation of grid-initiated building control strategies.
   c. Advanced micro-scale power grid studies where a community of buildings interact with each other and/or share energy from DGs to support higher level objectives of the modern grid.

2) Developing a set of performance indicators that can be used to quantify power performance of building energy systems and their control mechanisms for:
   a. Load assessment at building scale, and
   b. Selection of an intervening HVAC control strategy to be implemented as a 'response' to grid-initiated signals (e.g., DR).

## 1.9 Approach

The objectives of this work are addressed through:

1) Development of coupled thermal and electrical models. A loose coupling method is used to achieve this. In this approach, the building thermal model and electrical model are solved sequentially. First, multi-state ZIP models are structured as the

power models of specific loads (HVAC systems) in buildings. Second, a detailed building energy modeling tool, EnergyPlus is used to model thermal behavior of a building. After simulating the building, ZIP equations are solved for each thermal state or cycle of the system. Use cases are illustrated to show applicability of load characterization and coupled thermal-electrical models.

2) A set of performance indicators are defined by performing a top-down functional decomposition and bottom-up technical system aggregation approach. Through this a set of functional criteria are selected that can be expressed as explicit performance requirements. The reason for performance requirement specification is to ensure that a building system is capable of fulfilling the functional requirements at a defined level of performance. Performance indicators are then formulated for each performance requirement as a function of characteristics and parameters of building systems found to fulfill each functional requirement. Decision situations at building scale are sketched to indicate how these performance indicators can be used to support decisions at building scale in the context of DR. This shall also aid development of automated building energy and power management systems, which currently is lacking even in Auto DR programs.

## 1.10 Thesis Outline

After the Introduction, the second chapter goes over a Literature Review to cover current status of building energy modeling for building performance assessment studies, load modeling in the power system, grid modernization and concept of power efficiency, detailed building energy and power modeling for power studies, and finally gaps in knowledge. Chapter 3 describes implementation of a method for coupling of thermal and electrical models. Chapter 4 provides details of power consumers in buildings and introduces a performance framework used to systematically identify a set of performance indicators for power demand in buildings. In Chapter 5, the performance indicators defined are tested by developing a number of scenarios based on different control strategies. These scenarios are modeled and performance indicators identified in the previous chapter are used to assess and compare performance of these HVAC control strategies in terms of demand reductions. Discussion of findings, conclusions, and future work are presented in Chapter 6.

# 2. LITERATURE REVIEW

## 2.1 Performance Assessment and Quantification

Traditionally, performance was solely evaluated via financial measurements (Randor and Barnes, 2007). An example of that is the DuPont performance measurement model from the 1920's. Although DuPont and General Motors might have been the pioneers of measuring performance, the one dimensional approach to performance measurement in terms of efficiency to reduce cost lacks a strategic foundation and failed to provide data and information about quality, responsiveness and flexibility (Skinner, 1974). In the 1970's, performance requirements of the Western and Japanese manufacturers were significantly different. In the U.S., the focus was on efficiency while in Japan, it was equally emphasized on both efficiency and effectiveness (Randor and Barnes, 2007 & Salloum, 2011).

Design thinking in terms of performance (i.e., performance-based design) started in the 1960's in the disciplines of Systems Analysis and Operational Research (Ianni, 2013). The advancement from traditional performance measurement approach to the modern perspective in the areas of manufacturing and management enlightened the building industry as well. At the end of the 1960's, Markus (1969) discussed the role of building performance measurement and appraisal in design. The performance concept in building was defined by Gibson (1982) as "… the practice of thinking and working in terms of ends rather than means. … It is concerned with what a building or building product is required to do, and not with prescribing how it is to be constructed" (Gibson, 1982). A more detailed discussion on the background of building performance assessment and quantification is included in Chapter 4.

## 2.2 Building Energy Modeling

Building energy modeling and performance simulation have been used for energy performance assessment in different countries and regions to support building design studies, building energy policy energy policy and standards, utility incentives, climate data for energy performance modeling, and heat island and climate change modeling. In addition to these, building energy performance assessment has also been used for sustainability, retrofit evaluation, and building stock modeling. There is a special category of building energy modeling methods categorized as normative meaning that they are not based on expert driven models, but based on a standardized (hence the term normative) model constructed such that the outcome (performance indicator) is indicative of the real performance. Other categories include simplified, i.e. reduced order models and detailed, high fidelity models, typically requiring extensive modeling expertise.

Simplified building energy models are quasi-steady state models derived to estimate energy consumption of end users in a given building. These models are designed to calculate energy flows of a building at the macro level with a simplified description of a building. A well-accepted normative method is defined in the CEN-ISO standards under the Energy Performance of Buildings Directive (EPBD) as the standardized calculation methodology for energy performance calculation (ISO 2008; CEN/TC 2006). In this method, calculations of heat gains and losses are aggregated by transmittance heat transfer, ventilation heat transfer, solar heat gains, and internal heat gains (Figure 2.1). Simplified building energy models approximate energy performances of the building systems (e.g., HVAC, lighting, domestic hot water, fan, and pump energy) with a small number of macro-level inputs based on a simplified description of a building and its systems.

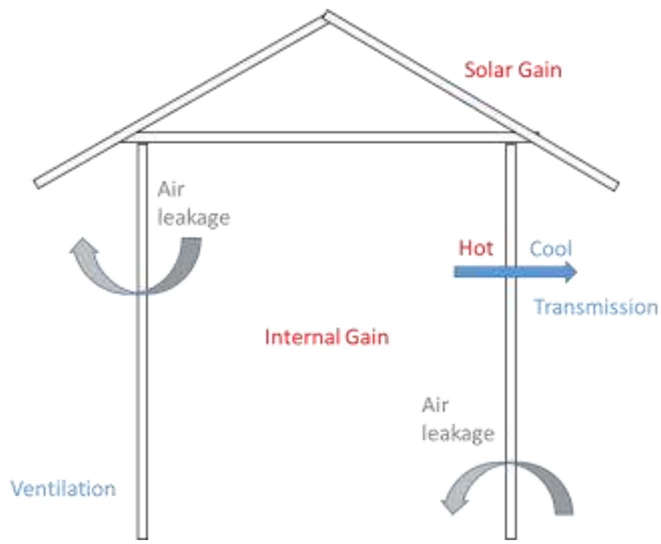


Figure 2.1 Simplified schematic of heat transfer and heat gains in a building

A simplified building energy calculation is based on the balance of heat gains and losses in steady state conditions. The calculation takes into account dynamic effects by introducing an internal temperature adjustment for heating and cooling intermittency and a utilization factor for the gain-loss mismatch. For each thermal zone, the total heat transfer $Q_{total}$ is calculated as the sum of heat transfer through transmission $Q_{trans}$ and ventilation $Q_{vent}$ each time step t:

$$Q_{total} = Q_{trans} + Q_{vent} \tag{2.1}$$

$$Q_{trans} = \sum_i (U_i A_i)(T_{in,setpt} - T_{out})t \tag{2.2}$$

$$Q_{vent} = \upsilon_{air}\, \rho_{air}\, c_{air}\, (T_{in,setpt} - T_{out})t \qquad 2.3$$

where, for each building envelop element i,

| | | |
|---|---|---|
| $U_i$ | *is* | the heat conduction coefficient, |
| $A_i$ | *is* | the area of surface element *i*, |
| $T_{in,setpt}$ and $T_{out}$ | *is* | the internal set-point and the external air temperature, |
| $\upsilon_{air}$ | *is* | the air exchange volume rate in each time step, and |
| $\rho_{air}$, $c_{air}$ | *is* | the density and specific heat capacity of air. |

The total heat gains $Q_{\text{gain}}$ of a building for a given time step can be calculated by summing the heat gains from internal heat gains $Q_{\text{internal}}$ and solar radiation $Q_{\text{solar}}$:

$$Q_{gain} = Q_{internal} + Q_{solar}, \qquad 2.4$$

where,

$$Q_{internal} = A_{total}\, (\varphi_{occupant}\, q_{occupant} + \varphi_{appliance}\, q_{appliance} + \varphi_{lighting}\, q_{lighting})t \qquad 2.5$$

and

$$Q_{solar} = \textstyle\sum_i (f_{sh,i}\, I_i\, A_{sol,i} - F_{r,i}\, q_{r,i})t \qquad 2.6$$

| | |
|---|---|
| $A_{total}$ | *is* the conditioned floor area |
| $\varphi_{occupant}, \varphi_{appliance}, \varphi_{lighting}$ | *are* the fractions of heat gains from occupants, appliances, and lighting |
| $q_{occupant}, q_{appliance}, q_{lighting}$ | *are* the heat production intensities of occupants, appliances, and lighting |
| $f_{sh,i}$ | *is* the shading factor |
| $I_i$ | *is* the solar irradiance, the mean solar radiation received over one time step, per square meter of collecting area of surface |

| | |
|---|---|
| $A_{sol,i}$ | *is* the effective collecting area of surface given its orientation, tilt angle, heat conduction, and convection coefficients (for opaque) and solar heat gain coefficient (for glazing) |
| $F_{r,i}$ | *is* the form factor between the building element and the sky |
| $q_{r,i}$ | *is* the long wave radiation flow rate from the element to the sky |
| $t$ | *is* the time interval |

Building thermal models typically require many of these inputs: location, heating and cooling equipment types and efficiencies, weather conditions (e.g., solar radiance, outdoor temperature, and wind speed), building properties (e.g., building area, non-glazed and glazed wall areas, roof and wall materials and their thermal conductance, solar heat gain coefficient, glazing type, material, and solar transmittance, and air flow rates), and control setpoints and schedules. In high-fidelity building energy modeling engines such as EnergyPlus$^{TM}$ (DOE, 2015), the inputs are similar to those needed for simplified models. However, more inputs are required to define the buildings and their subsystems. In other words, inputs of simplified models are a subset of detailed building energy models. Only detailed models can address multi-zone buildings, various types of heating and cooling equipment, details of air distribution systems, and airflow between zones. Use of detailed models for grid studies should be carefully considered to avoid unnecessarily elevating the cost of modeling, computation, and post-processes associated with such models.

## 2.3 Load Modeling in the Power System

Buildings are a constituent part of the power system with small or large electrical loads. ‘Load’ in the power system may carry different meanings according to IEEE (1993). The definition of load is a device or equipment connected to the power system consuming power (IEEE, 1993). One of the most fundamental studies related to any system is the calculation of the steady state behavior. In the power system studies, this calculation is the steady state power flow or load flow. Load flow analysis essentially involves determination of the steady state voltages at each node under certain generation and consumption (i.e., loading) conditions using methods such as Newton-Raphson. In load flow studies, a load model is a mathematical representation of the relationship between a bus voltage (magnitude and frequency) and the active and reactive power (IEEE, 1993). In other words, a load model calculates the active and reactive power at each node to be used in the power flow study which determines the 'flow' of power to obtain complete voltage angle and magnitude for each bus in a power system.

In the current power system, load models represent the aggregation of hundreds or thousands of individual component devices such as motor, lighting, and electrical appliances, which are usually modeled at representative substations or feeder levels (Choi et al., 2006; Sadeghi and Abdollahi, 2009). In this work, load is referred as a power consuming device that serves the building thermal demand. Such devices are commonly known to as building energy systems. In power system studies, load types can be categorized as shown in Table 2.1.

Table 2.1 Load types in the power system.

| **Load category** | **Example** |
|---|---|
| Those with ‘fast dynamic’ electrical and mechanical characteristics | Induction motors |
| Those with significant discontinuities as response to voltage excursions | Motor contactors that drop open during faults and voltage swings, removing load from the system, and motor overload protection that removes stalled motors from the system after about 10 seconds |
| Those without significant discontinuities or time lags as response to voltage excursions | Very small motors, incandescent lighting, and uncontrolled resistive loads. |
| Those with ‘slow dynamic’ characteristics | Loads controlled by thermostats and manually-controlled loads that are initially constant resistance but change to constant power over a 10-20 minute period after a change in voltage |

Load models can be categorized as dynamic and static load models. Dynamic models are those that express the active and reactive powers at each time step as functions of the voltage magnitude and frequency at past time steps (usually the current timestep is also included). Differential equations have been used to represent such models, but dynamic load models in general are not employed as commonly as static load models. Static load models are those that express the power (active and reactive) at each timestep as a function of voltage and frequency at that timestep. In addition to representing static load devices such as lighting, these models are also usually used for approximation of dynamic load devices such as motor-driven loads (IEEE, 1993).

Approaches adapted for load modeling can be categorized as component-based (i.e., physically-based) methods or measurement-based ones (Ranade et al, 2001; Renmu et al., 2006). *Measurement-based approaches* involve direct measurements of the sensitivity of the load power (both active and reactive) to voltage, frequency, and weather variations by placing monitors or sensors at different substations and feeders. Findings are then directly used to construct load models or indirectly by identifying parameters that can be used in load modeling (Renmu and Germond, 1984; Ranade, 2001; Sheng et al., 2004, Han et al., 2009). The main advantage of measurement-based approaches is the availability of actual data from the system under study and the possibility to track seasonal variations as well as deviations from normal operation. However, there are also disadvantages which include: applicability of using data gathered at one location may not be plausible at another location (i.e., not scalable), not easy to determine load characteristics over a wide range of voltage and frequency data, and also accounting for changes in load behavior under different conditions (e.g., weather) requires on-going measurements under these conditions. *Component-based approaches* involve developing a composite load model from information of its constituent parts, i.e., mix of classes at the substation, composition of each of those classes, and main characteristics of each single load component (Renmu et al., 2006). So, in this approach, load models are aggregated models of the individual load components, which their characteristics are determined by theoretical and laboratory analyses (Louie et al., 2003). The main advantage of component-based approaches is that they do not require field measurements and are adaptable to different systems and various conditions (i.e., they are scalable). The disadvantage is that load class mix data varies from bus to bus and is dependent on weather and time, and therefore, it is required to update the load class mix data for each bus of the system.

# 3. COUPLED THERMAL AND ELECTRICAL MODELING

## 3.1 Introduction

In 2011, residential and commercial building sectors used 38% and 36% of electricity sold in the United States respectively (EIA, 2012). Buildings as the major consumers of electricity, play a significant role in the design, operation, planning, and management of the power system. However, to reduce the complexity of power models, buildings are traditionally modelled as aggregated load models and represented as "dumb" nodes in the power grid.

In the research and studies related to building performance assessment, the focus has been on evaluating energy efficiency to design more energy efficient buildings whereas the instantaneous power consumption of systems has been overlooked. This is important because it has traditionally been critical in the electricity system to have a realistic forecast of buildings' demand (both short term and long term) for adequate power planning and management. It is becoming even more important and critical to model and study buildings in more detail in the power grid because of all the changes the electricity system is going through. Recent efforts for grid modernization and the need to use buildings as resources to support the power grid have raised the interest to have better understanding of building energy and power performance in the power system, which cannot be achieved without developing more detailed load models.

Concerns about demand peaking have increased the number of studies related to large scale building stock modelling to capture peak load. However, power variations as a function of electrical characteristics of systems are not yet captured in conventional building energy models. The lack of modelling electrical energy limits studies related to reactive power and peak load management using strategies such as conservation of voltage reduction (CVR). This limitation also contributes to uncertainty in energy consumption calculations carried out in the absence of voltage variations. Inaccuracy in energy and power performance evaluations affects design decisions, HVAC systems sizing, operation, and control.

Historical energy usage data in the U.S. indicate that although we are moving towards energy efficiency goals, our buildings are consuming more power during power peak hours. Peak-to-average electricity demand ratio has increased in New England and the same trend is present for many other U.S. regions (EIA, 2012). One potential cause of that could be reduction of average consumption resulted by implementation of energy efficiency measures and renewables. This effect is also predicted and presented using 'duck curves.' The emerging technologies of the modern grid and integration of intermittent and unpredictable generators (e.g., wind and solar) make it more critical to investigate different factors that affect power performance of systems to better understand load profile of buildings. This is important for effective load management and control.

Consolidated Edison Company of New York (Con Edison), a regulated utility providing electric service to most of New York City (NYC), has published a chart that shows the number of hours in a year vs. load or power consumption in MW. As shown in

Figure 3.1, the load is about 7600 MW or less for most hours in the year. However, the curve presents a sharp increase in load for a small number of hours in the year; the consumption is larger than 12,000 MW for only 36 hours in the year (Logsdon, 2013). This represents a power concern (i.e., instantaneous power consumption during peak hours) and not just energy (i.e., power use over a period of time).

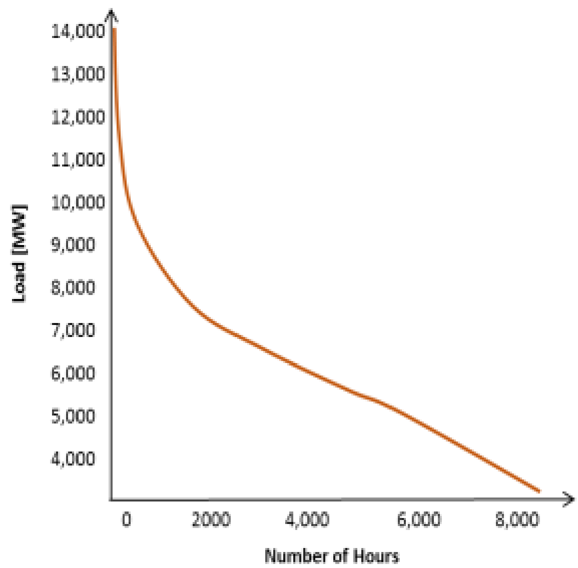



Figure 3.1 Load duration curve (Logsdon, 2013).

A simple example to show the importance of studying instantaneous power consumption is to compare power and energy usage in two different scenarios. In the first scenario, there are ten 200W fans in a building, but only one comes on at each hour during the operation hours (their duty cycles alternately). In the second scenario, all ten 200W fans cycle on at the same time and run for one hour. In both scenarios, the energy consumption is 2000 Wh at the end of the day assuming 10 hours of operation. However, in the first scenario, the instantaneous power consumption is 200 W at each hour while in the second scenario, it is 2000W, which is 10 times more. This is the underlying cause of spikes in power demand during the ‘peak hours.’ Although we can capture the power peaks in this simple example using current energy assessment methods, this study is concerned with understanding impact of electrical performance of systems and more specifically voltage variations on peak power. This would support control and management of power peaks at system and device level in buildings.

The major concerns about peak demand are economic efficiency, environmental quality, fuel security, and facility siting (Koomey et. al, 2002). According to ConEdison results (Logsdon, 2013), peak power consumption hours occur during 36 out of 8760 hours in a year. Utilities size their systems based on peak load. Therefore, the generation, transmission, and distribution infrastructure that supports peak load, sits idle for more than 99% of time in the year. Servicing peak loads require the utility’s highest marginal cost plants, which are usually inefficient and air polluting generators as well. In addition, these back-up generators are fired by either natural gas or fuel oil, raising issues of fuel security and price instability respectively for each fuel type (Koomey et. al, 2002).

We believe the instantaneous power performance and challenges related to it should also be evaluated and addressed in studies carried out by the building science and technology disciplines. As to work related to urban and large scale building energy assessment grows, power concerns should not be left out. The instantaneous power use (kW) is a challenge of smart cities as much as their energy consumption (kWh) is. This is concerned with capital resources rather than just benefits of energy savings of individual building owners and facility managers.

To better understand the power efficiency of building systems, the first step is to construct models that enable a better evaluation of buildings power performance in the electricity system. Coupling of power models constructed using electrical parameters (e.g., voltage) with existing thermal models allows assessment of power efficiency of building systems as a function of their electrical behavior and performance in addition to the current energy evaluation methods that are carried out based on the thermal behavior of buildings and their energy systems. Systems in buildings can only be studied in association with the building load (thermal demand, light and appliance load etc.) and a control system that executes the way that the systems are deployed in order to satisfy the thermal demand. In many cases the control system modifies the thermal demand in the process. This is further detailed below.

One of the advanced technologies that is involved with the use of building assets for power management is Auto-DR using Open Automated Demand Response (OpenADR) developed by the Demand Response Research Center (DRRC, 2015). Auto-DR is widely adopted and implemented by utilities. In Auto-DR, different strategies are used for HVAC control, which range from global temperature setpoint adjustment to supply air temperature increase, supply fan speed reduction, duct static pressure reduction, chilled water temperature increase, to rooftop unit shutdown, chiller demand reduction, boiler lockout, and pre-cooling of building thermal mass (Kiliccote et al., 2006a). Although this represents the potential of buildings to provide support to the grid, we lack adequate models that can be used to evaluate and compare the impact of a wider range of strategies including ancillary services such as frequency regulations and CVR (MacDonald et al., 2014 and

Zhao et al., 2015). Furthermore, design and evaluation of power efficient HVAC systems (e.g., pump motors) that can provide maximum benefit to the grid while reducing demand charges for buildings, cannot be achieved without the right system modelling and simulation tools.

The main objective of this chapter is to estimate a building's load profile as a function of voltage variations coupled with thermal response of the building. To fully capture the behavior of buildings in the power system and study the impact of grid technologies on building energy performance, power models that capture electrical characteristics of buildings (e.g., voltage and current) are developed in this work. These power models also improve current building energy simulations by capturing electrical behavior of systems in addition to their thermal behavior. EnergyPlus is used as a platform to implement these models. However, these voltage-based power models can be coupled and integrated with any building energy simulation tool.

Modelling power as a function of voltage enables studies related to cascading power failure due to excessive reactive power, conservation of voltage reduction (CVR) as a demand response method for DSM, and uncertainty quantification in thermal energy calculated in absence of electrical variations. Thermal-electrical models of buildings support more effective design, selection, and operation (i.e., control) of motor-driven building systems for energy and power conservation goals in addition to better planning and management of the electricity system.

## 3.2 Background

It has long been known that variations in the power system affect power quality and energy consumption of building electricity users. Hood (2004) looked into the effects of voltage variations on power consumption and running cost of domestic appliances. This study reported that voltage increase results in power increase (kW) in most appliances, but it does not necessarily translate into an increase in energy consumption (kWh). For example, in resistive loads, a voltage rise of 10% resulted in more than 20% increase in power, but less than 20% in energy. This shows that power cannot always be directly derived from thermal energy calculations e.g., those carried out in building energy simulation tools.

The research and literature related to electrical modelling of systems coupled with thermal energy modelling is limited. Kelly (1998) discussed the lack of a power flow modelling capacity in building simulation tools and addressed this by developing a network solver (i.e., Newton-Raphson iterative solver) and coupling that into ESP-r modelling and simulation tool. In this method, the electrical network is solved simultaneously with the other constituents of the building thermal model. The limitation of this method is that the load calculation is still only based on thermal characteristics of the building and not electrical characteristics (e.g., voltage) and hence not capable of capturing impact of voltage variations on performance of building energy systems. Another limitation or disadvantage is that it was developed to the specifications of ESP-r and not with a generic method that can be used in wider range of building and grid tools. It is also mainly concerned with calculation of power flow for applications that involve on-site power generation such as PV or small CHP system.

On the power grid side, some utilities model 'loads' in the power system, which are usually simplified and not coupled with thermal characteristics of buildings (Kosterev, 2008; IEEE, 1993; IEEE, 1995). Schneider et al. (2011) looked into integration of thermal and electrical models and used these for power distribution simulation. However, the building thermal models used in this work were derived from the equivalent thermal parameter (ETP) approach. These simplified models can be used to model only single zone (e.g., residential and small commercial) buildings. It is well known that more detailed load models are required to understand the behavior of a building and its systems (e.g., HVAC) in the power grid (Schneider et al., 2011). To evaluate power efficiency and assess the impact of system power profile, the electrical characteristics of systems should be modeled and simulated in smaller time scales (e.g., minutes) compared to hourly energy calculations that are normally carried out to assess energy performance of buildings. The system collapse of 1987 in Tokyo was partly because of underestimating the characteristics of the reactive power consumption of air-conditioning loads (IEEE, 1993). The cascading outage that took place in the North American Eastern Interconnection (interrupting about 63GW of load which is about 11% of the total load distributed in the Eastern Interconnection) was also associated with significant amount of reactive power and inadequate understanding of the system behavior (He, 2011). In load flow studies, a load model is a mathematical representation of the relationship between a bus voltage (magnitude and frequency) and the active and reactive power (IEEE, 1993). Load modelling and load characterization studies have been performed for a long time. In 1992, an IEEE Task Force published a paper on “Load Representation for Dynamic Performance Analysis,” summarizing the current status on power system load modelling (IEEE, 1993). Definitions of basic load modelling concepts were explained and the importance of further developments in load modelling was discussed.

In the current power system, load models represent the aggregation of hundreds or thousands of individual component devices such as motors, lights, and electrical appliances, which are usually modeled at representative substations or feeder levels (Choi et al., 2006; Sadeghi and Abdollahi, 2009). Load models used in the power system can be categorized as dynamic and static load models (IEEE, 1993). Dynamic models are those that express the active and reactive powers at each time step as functions of the voltage magnitude and frequency at past time steps (usually the current timestep is also included). Differential equations have been used to represent such models, but dynamic load models in general are not employed as commonly as static load models. Static load models are those that express the power (active and reactive) at each timestep as a function of voltage and frequency at that timestep. In addition to representing static load devices such as lighting, these models are also usually used for approximation of dynamic load devices such as motor-driven loads (IEEE, 1993). These static load models, known as ZIP models, are the most commonly used methods to model electrical systems in the power grid (Bokhari et al., 2013; Sadeghi and Abdollahi, 2009; Schneider and Fuller, 2010; Schneider et al., 2011).

Coupling thermal and electrical behavior of buildings is a challenging task. This is because of the very distinct thermal, electrical, and electromagnetic properties of systems and motors with different governing physics. One way to achieve this is by adding multi-state time variant power models (i.e., ZIP models) to the building energy thermal model (Schneider et al., 2011). Literature suggests that using a multi-state ZIP model allows the complete behavior of the load to be represented and the impact be assessed. These models are limitedly used for detailed end use load modelling of systems such as residential heat pump, appliances, and plug-in electric vehicles (PEVs) (Bokhari et al., 2013; Schneider et al., 2011, Sortomme et al., 2012). In the case of heat pump for instance, the model was constructed for different operating states: off, cooling, heating (Schneider et al., 2011). These can also be used to describe electric behavior of more complex systems such as commercial HVAC systems. The main challenge is that electrical data is not readily available at system and especially at component level (e.g., fan, pump).

### 3.3 Modeling Methodology

In this work, 'load' refers to a power-consuming device that serves the building thermal demand and is considered to be part of the building energy systems. To model load, ZIP models are used to describe the static behavior of electrical loads. A ZIP model is a static model that represents the power-voltage relationship as a polynomial equation of voltage magnitude and consists of three load components: constant impedance (Z), constant current (I) and constant power (P). There are different forms of mathematical representation of the ZIP model. In the form used in this study, the frequency variations are not considered.

These models can be used to describe real power (Equation 3.1) and reactive power (Equation 3.2) consumption of loads as a function of the system voltage.

$$P = |P_0|.[Z_{\%}.Cos(Z_\theta).\frac{|V^2|}{|V_0^2|} + I_{\%}.Cos(I_\theta).\frac{|V|}{|V_0|} + P_{\%}.Cos(P_\theta)] \qquad 3.1$$

$$Q = |Q_0|.[Z_{\%}.Sin(Z_\theta).\frac{|V^2|}{|V_0^2|} + I_{\%}.Sin(I_\theta).\frac{|V|}{|V_0|} + P_{\%}.Sin(P_\theta)] \qquad 3.2$$

$$Z_{\%} + I_{\%} + P_{\%} = 100 \qquad 3.3$$

Where,

$P$, real power consumption of load;

$P_0$, apparent power of load at nominal voltage;

$Q$, reactive power;

$Q_0$, nominal reactive power;

$V$, actual terminal voltage;

$V_0$, nominal terminal voltage;

$Z_{\%}$, percent of the load with constant impedance;

$I_{\%}$, percent of the load with constant current;

$P_{\%}$, percent of the load with constant power;

$Z_\theta$, phase angle of the constant impedance;

$I_\theta$, phase angle of the constant current component;

$P_\theta$, phase angle of the constant power component.

In this work, multi-state ZIP models are developed for an air handling unit (AHU) and a roof top unit (RTU) with heat pump. Then, these models are used to model multi-state time variant power models of similar systems in other buildings. In the time-variant load representation, the coefficients of the ZIP model remain constant for each device, but the active and reactive power consumptions of the load change with the terminal voltage. Therefore, they can describe the real and reactive power consumption of loads as a function of system voltage. This would allow to evaluate impact of voltage variations on power use of buildings and enables comparison of that with power calculations carried out in building energy simulation engines that are solely based on thermal characteristics of systems.

The polynomial equation of voltage magnitude is used to represent the power-voltage relationship of systems selected. To do this, an AHU was monitored in a controlled lab environment. Data from an RTU unit and a chiller (in field under normal operation) were also provided by the facility managers. Time-variant data for energy consumption, power use, and voltage were recorded. 10-second data were collected for the AHU, 5-minute data for the RTU, and 30-minute data for the chiller. Data was gathered at different time intervals for systems under study because voltage data is not readily available for in field systems and it is not easy to access such data. Data collected from the AHU fan is shown in Figure 3.2. Although fan is not a resistive load, the motor has really low torque and therefore, the power follows voltage. Such loads are referred to as voltage leading.

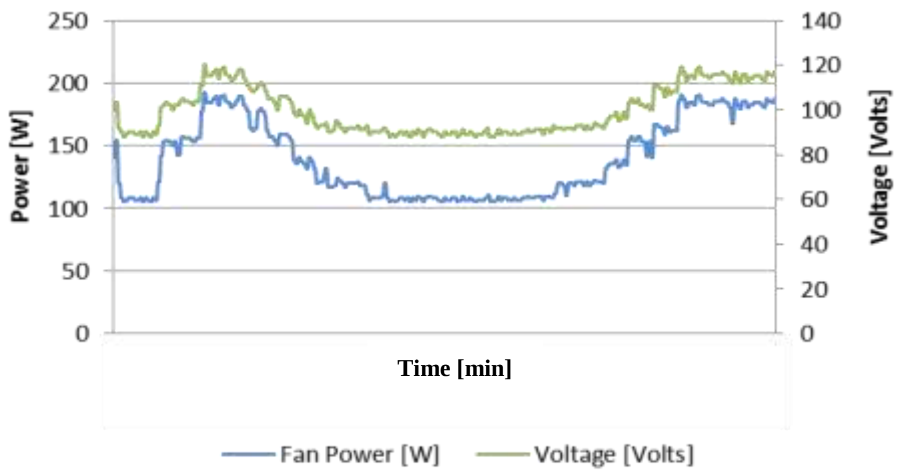



Figure 3.2. Time series voltage and power data of AHU fan.

Data collected from the RTU does not reveal the same behavior as the AHU fan. First, data was not collected for each motorized component in the RTU. This was because of a data collection limitation; sub-systems are usually not instrumented. Secondly, these systems have inductive motors with higher torque. In such motors, because of the magnetic field, voltage does not lead the power; such loads are referred to as voltage lagging. Figure 3.3 below shows the behavior of voltage and power in relation to each other.

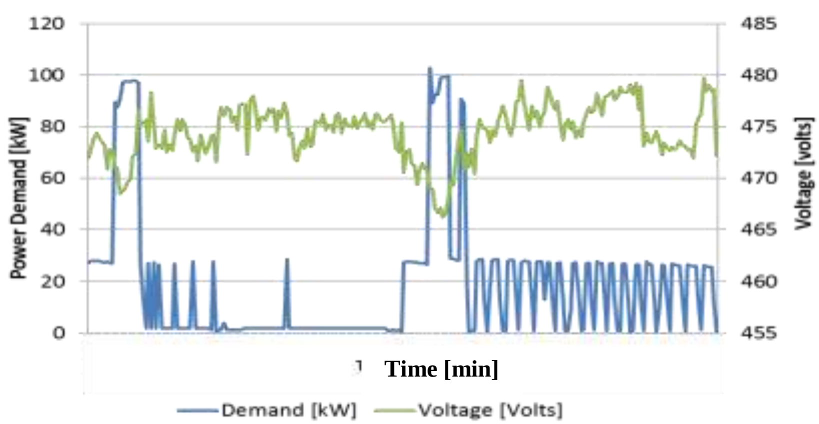



Figure 3.3 Voltage and power data collected from RTU.

Time series data collected provided a discrete voltage profile, which was then used to construct a voltage dependent power model for each load using the polynomial equations of voltage magnitude in Equations 3.1 and 3.2. To determine the ZIP coefficients, a constrained least squares fit approximation to the measured values are estimated. The objective used to find the best fit is to minimize the residuals, *J(x)*, defined as:

$$J(x) \quad = min \sum_{i}^{n} \sqrt{\left(\acute{P}i - Pi\right)^2} + \sqrt{\left(\acute{Q}i - Qi\right)^2} \tag{3.4}$$

After finding the best fit ZIP coefficients, they are inserted in Equations 3.1 and 3.2 to construct voltage dependent equations for active and reactive power of each system. Figure 3.4 and Figure 3.5 depict the estimated real and reactive power of the AHU fan plotted. The residual for this estimation was 2.47.

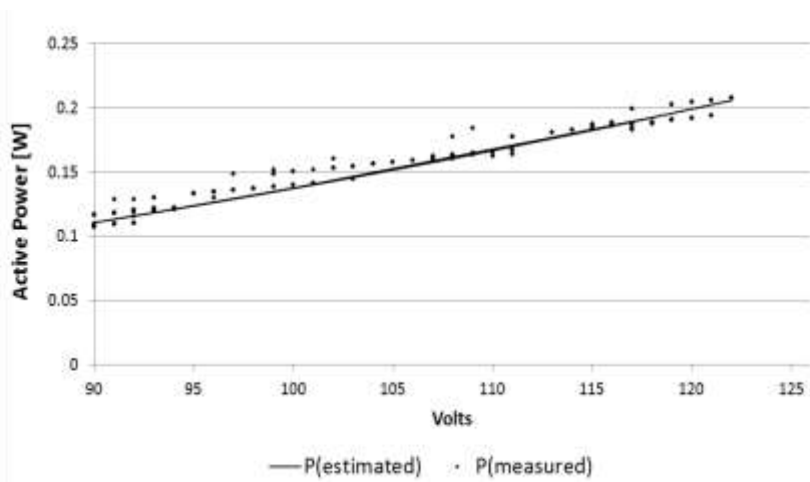



Figure 3.4 Estimated vs measured real power consumption of AHU fan.

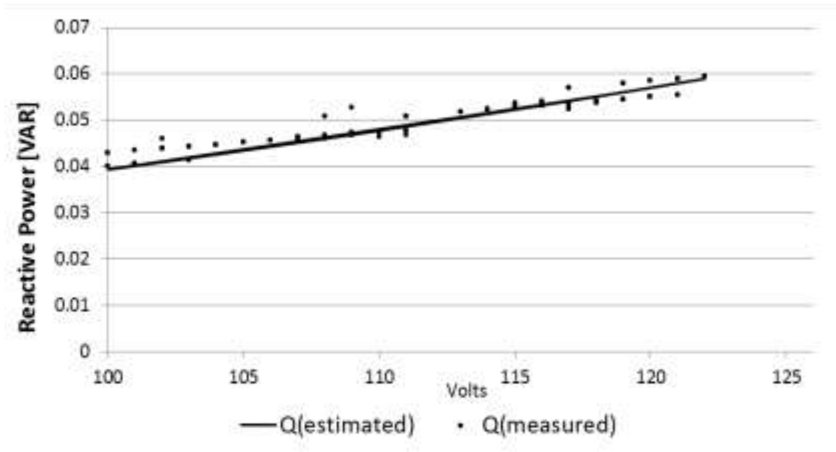



Figure 3.5 Estimated vs measured reactive power consumption of AHU Fan.

Figure 3.6 and Figure 3.7 *s*how the estimated real and reactive power of the RTU plotted. The residual for this estimation is 12268. The large residual and the plots clearly show that in this case, the power is not following the voltage all the time although at most time-steps voltage is still leading the load. This also indicates that the system has more than one sub-system and if data were collected at each of those components, a more accurate model could be derived for the RTU.

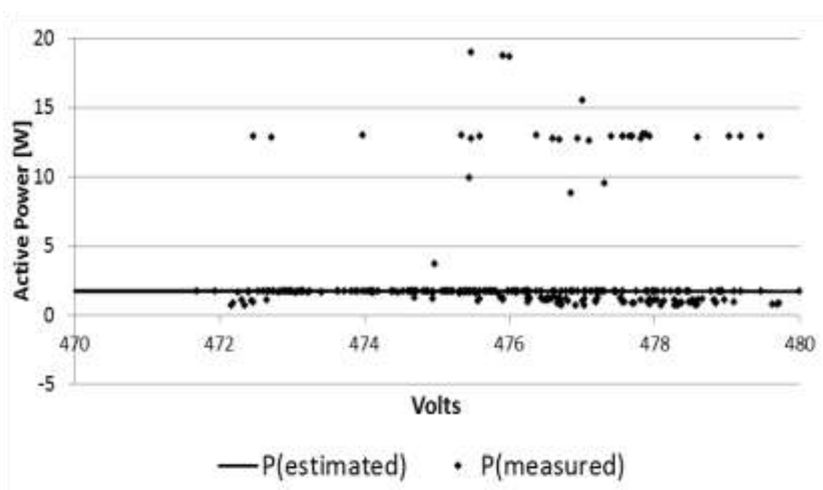



Figure 3.6 *Estimated vs measured active power consumption of RTU*

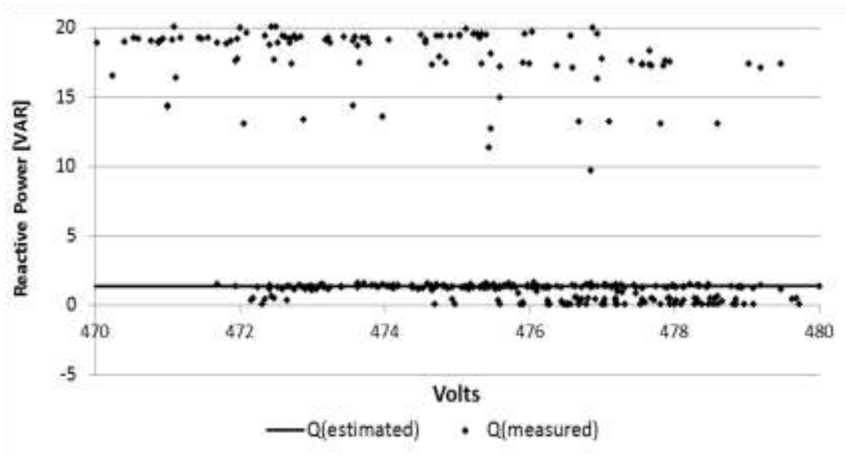


Figure 3.7 Estimated vs measured reactive power consumption of RTU

## 3.4 Coupling or Integration of Electrical and Thermal Models

The coupling method used here to integrate the electrical and thermal models can be considered as ‘loose’ coupling. The terms ‘loose’ and ‘tight’ coupling are used in different disciplines and scientific communities to describe the interdependency, information flow, and rate of information delivery between two models, systems, simulators, tools, or software modules. Coupling is used when there is a need to connect two systems with different physics, characteristics, level of fidelity, or scale (temporal or spatial).

In loose coupling, the underlying equations of a system are first solved and solutions (i.e., outputs) obtained are transferred to the second system to be solved. The advantage of this approach is that it allows for independent models to be coupled with relatively minor changes to those models. Hence, each model can have its own underlying equations and solution strategies tailored for its domain. A disadvantage of loose coupling is that one solver or model should wait for the response from the first one and this might take longer time to be executed (Novascone et al., 2013).

In tight coupling, usually a single system of equations is defined and solved for the full set of coupled models. The unified system solves the equations of both models simultaneously. The advantage of strong coupling between the physics of models is that this approach can have faster convergence rates compared to loose coupling. The main disadvantage of this is approach is that it requires tighter coordination between the models (Novascone et al., 2013). Another disadvantage is that the interdependency of models increases in this approach; hence, individual models cannot be easily broken down into separate processes to be computed independently.

Both types of coupling methods have been used in different applications with distinct characteristics. The definitions of ‘loose’ and ‘tight’ coupling vary slightly depending on the application. For instance, in composite structure simulations, models of different size and fidelity have been coupled or connected for multi-scale analysis. The interrelation between these levels of analysis is classified as loose coupling and tight coupling. In ‘loose coupling’ spatially separated models are used (i.e., distinct simulators) solving a global and a local or detailed model *sequentially*. In contrast, in ‘tight coupling,’ numerical methods *simultaneously* solve the systems of equations corresponding to the global and local models. Usually loose coupling is synonymous with one-way information transfer from one model to the other, however, in tight coupling, the transfer is bidirectional (Talreja & Varna, 2015). In geographical information system (GIS), tight coupling also refers to the simultaneous operation of systems allowing direct inter-system communication during the program execution. In loose coupling, one software is used to execute the model and store outputs. The stored results are then transferred to another software for visualization

(Marceau & Benenson, 2011). In industries such as aerospace engineering, coupling is used to calculate the structural dynamics and aerodynamics of systems simultaneously. Tools used for Computational Fluid Dynamics (CFD) are coupled with Computational Structural Dynamics (CSD) to study the fluid-structure interactions. In this method, the flow and the structure equations are treated separately. The fluid field is first computed and then integrated or coupled with the structure movement calculations using synchronization procedure in space and time (Wang & Lin, 2008). In computational sciences, a coupling is considered to be 'tight' if performed at every time step and loose if performed at longer time steps. The type of coupling between two constituent models can be determined by the ratio of the models' timesteps to the interval of time between coupling interactions. Two models that couple at every timestep have a ratio of 1 and are considered to be tightly coupled (Larson, 2009).

In summary, tightly coupled models show a high degree of non-linearity. This indicates that tightly coupled models can be thought of as a single system of equations. On the hand, loosely couple models are more linear and can be broken down into separate set of equations and calculations that are combined to obtain a final solution. The common features and characteristics found after reviewing definitions of loose and tight coupling methods in different areas are summarized in Table 3.1.

Table 3.1 Features of loose and tight coupling methods.

| Coupling type | Computation | Information flow | Rate of information delivery |
|---|---|---|---|
| **Loose** | Sequential | One directional | Long |
| **Tight** | Simultaneous | Bi-directional | Short (every time step) |

The thermal and electrical models combined in this work follow definition of loose coupling approach. This is because both sets of models, which are the building thermal model and the ZIP model are solved sequentially. The thermal model of the building is first solved and states or cycles of the system are used to solve the ZIP equations. In this approach, the interaction or communication between the two models does not happen at every time step but at every thermal cycle of the simulated system.

EnergyPlus is a detailed building energy simulation program that is widely used in the U.S. by architects, engineers, and researchers to evaluate building thermal energy performance. Similar to other transient building simulation models, EnergyPlus emulate energy performance of systems by solving the full set of dynamic heat balance equations using numerical methods. However, the energy and power consumption in buildings as a function electrical characteristics (e.g., voltage) cannot be captured in transient simulation tools such as EnergyPlus. Figure 3.8 shows energy use of an AHU modeled in EnergyPlus (similar AHU as the one used earlier to derive the ZIP models described in Equations 3.1 and 3.2, but not the same). As it is depicted, momentary variations in power are not captured when power (kW) is derived from thermal energy (kWh) simulated using building thermal energy simulation engine. Figure 3.9 represents the actual metered power data and how it compares with power simulated using EnergyPlus. Therefore, using only thermal energy analysis methods do not allow us to find the uncertainty and error introduced because of voltage variations in the power system. The impact of such errors on energy usage and more specifically on instantaneous power consumption is not well understood.

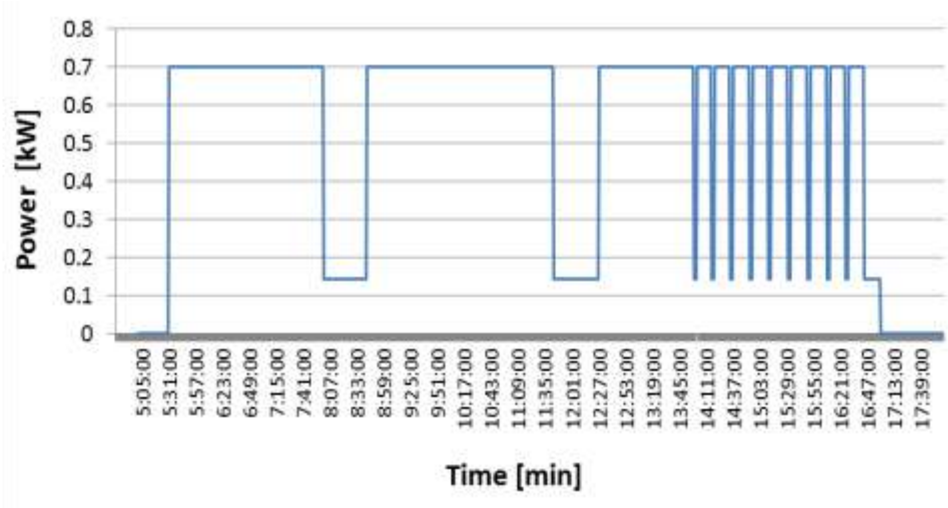



Figure 3.8 Power use of an AHU modeled in EnergyPlus

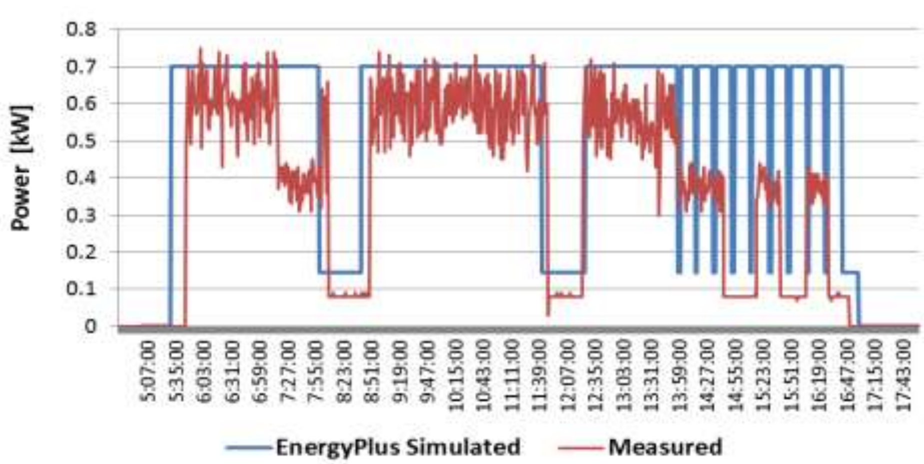



Figure 3.9 Measured vs. EnergyPlus simulated power

One way to tackle this problem is to use the voltage dependent ZIP power models to calculate the instantaneous active and reactive power as a function of voltage within each thermal cycle and operation mode of the system as modeled in EnergyPlus. Although this introduces a loose coupling of electrical-based power models with existing thermal models, it provides a simplified method to generate some information about impact of voltage variations on instantaneous power use of electrical and thermal systems in buildings, which cannot be captured in current building simulation tools.

## 3.5 Results and Discussion

Figure 3.10 depicts how measured power data of the AHU fan compares with simulated (EnergyPlus) and estimated (multi-state ZIP + Eplus). As shown, the multi-state ZIP model following load cycle better captures instantaneous variations in power as a function of voltage.

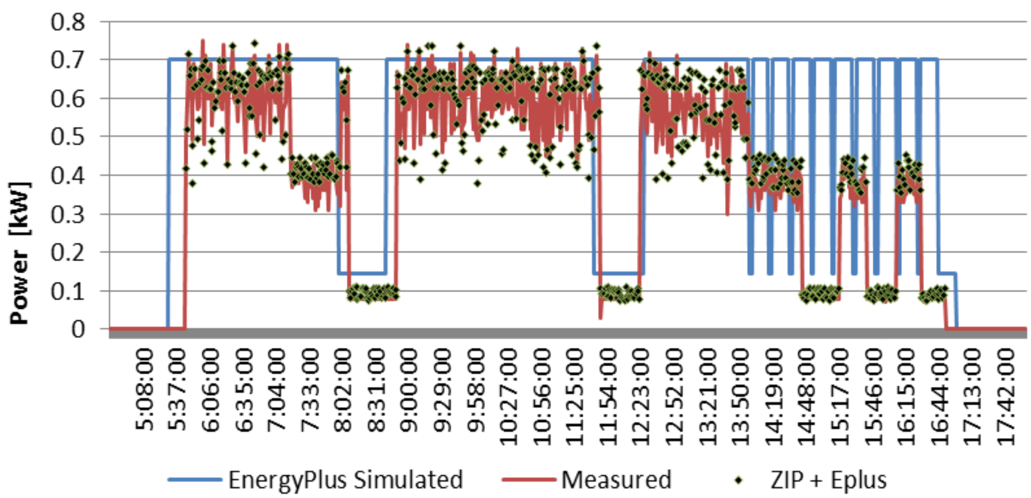



Figure 3.10 Measured and simulated power compared with the power calculated using both thermal and electrical models

Mean square error (MSE) was used to measure the error between power measured, simulated, and estimated (Equation 3.5). Results are summarized in Table 3.2.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\acute{P}i - Pi\right)^2 \qquad 3.5$$

Table 3.2 MSE calculated to measure error between simulated and measured power as well as estimated (ZIP + thermal) and measured

| SYSTEM | MSE (Simulated and Measured) | MSE (Estimated and Measured) |
|---|---|---|
| AHU Fan | 0.0744 | 0.002 |

As the results indicate, the MSE of simulated vs measured and that of estimated (ZIP + thermal) vs measured are both small. However, the absolute error at each timestep is larger if we compare simulated results with measured data. Estimated instantaneous power usage is closer to measured values. Furthermore, it should be kept in mind that the main point here is capturing the momentary variations of power as a function of voltage and not necessarily the accuracy of calculations. EnergyPlus would not be able to respond to voltage changes at all while ZIP models can show the magnitude of change in power as a measure of voltage. This is useful for studying applications such as CVR that are concerned with achieving energy efficiency by controlling voltage using either a central control signal (i.e., from the utility) or a building level signal from building automation systems used to manage load.

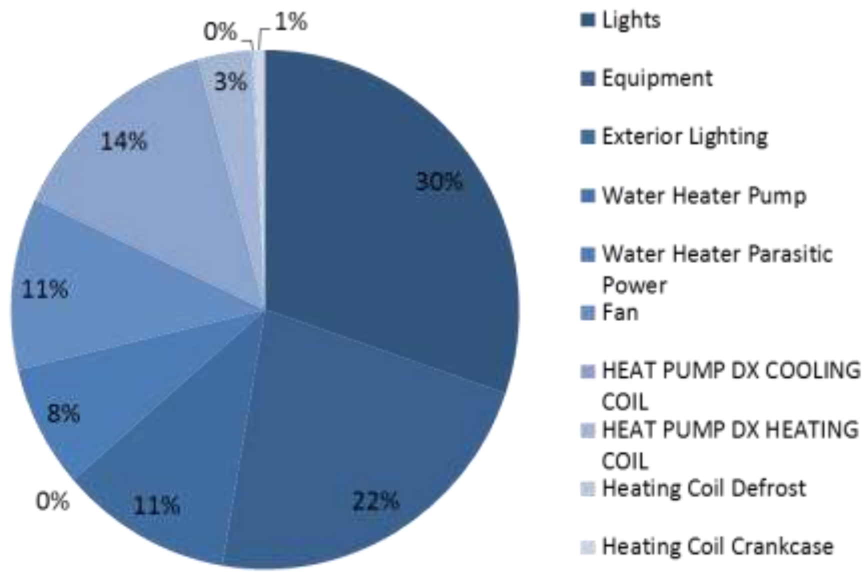
The next section gives an overview of building loads that are voltage dependent to estimate the percentage of load that can be controlled by toggling voltage during peak hours.

## 3.6 Application in Demand Management

Knowing that voltage dependent load models can be used to generate more information about instantaneous power behavior of electricity end users in buildings, it would be helpful to better understand load types in buildings. In general, load can be categorized as voltage leading or voltage lagging. Resistive loads are voltage leading because power variations follow voltage variations. Therefore, reducing or increasing voltage affects power consumption of such loads. On the other hand, inductive loads are considered to be voltage lagging because the magnetic field of the stator in an inductive motor creates a torque to rotate the shaft. Hence, such loads are not only voltage dependent and their power consumption cannot solely be controlled by varying voltage.

Figure 3.11 and Figure 3.12 show electricity consumers in a small office with heat pump and small office with RTU. Figure 3.13 presents those in a large office with chiller. Data shown are derived from DOE prototype buildings modelled in EnergyPlus. Loads in buildings are characterized as voltage leading (e.g., resistive load) or voltage lagging (e.g., inductive load) to see what percentage of instantaneous power use in buildings with similar specifications and layouts can be managed by controlling and varying voltage using strategies such as conservation of voltage reduction (CVR).

It was found that, roughly, about 35% of load in these commercial buildings can be categorized as voltage leading. This means using CVR methods (a strategy used by utilities for energy conservation), only about 35% of load would be responsive to the control signal.



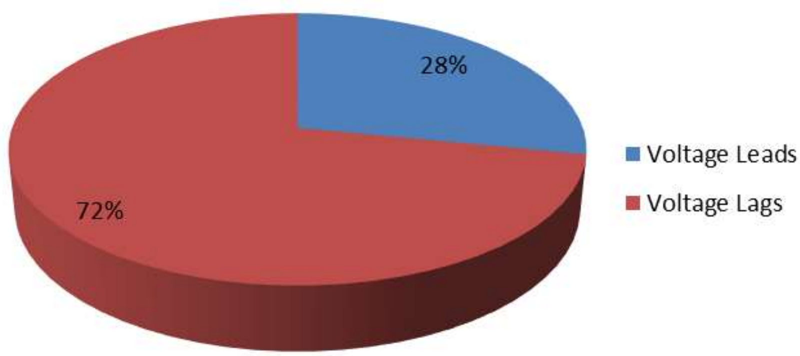
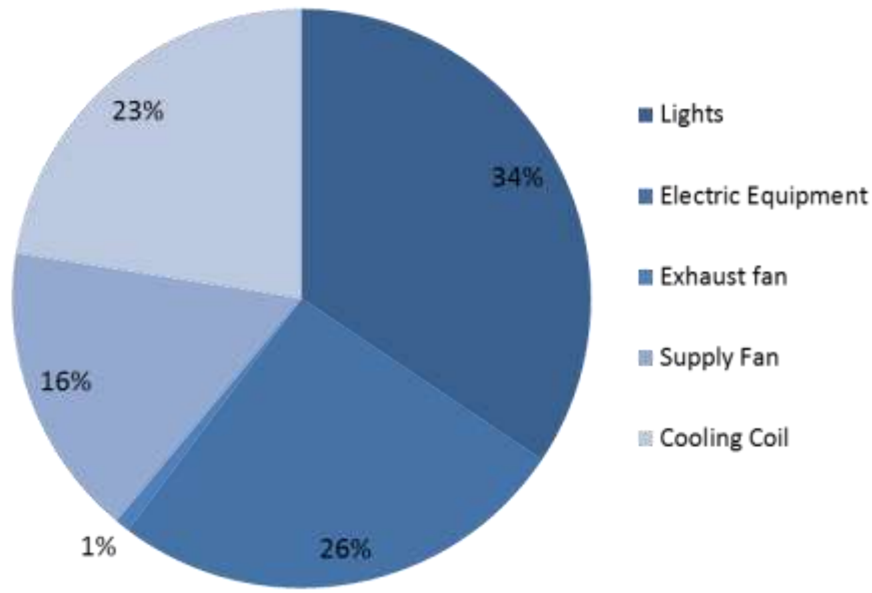




Figure 3.11 Small office with heat pump (28% of load is voltage leading and 72% is voltage lagging)



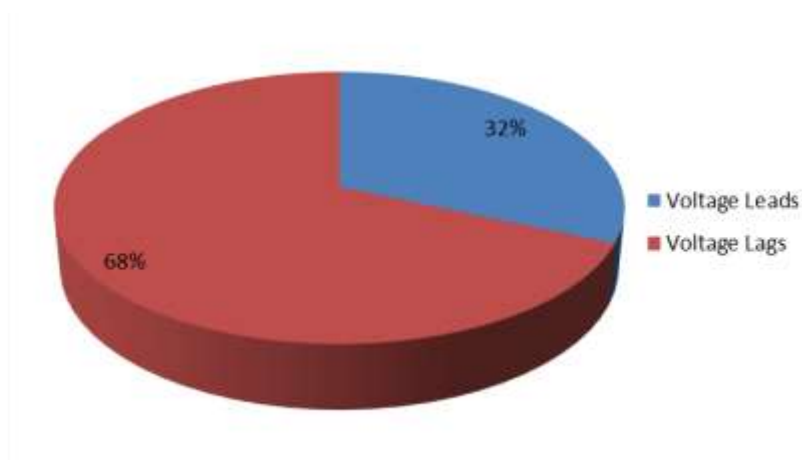
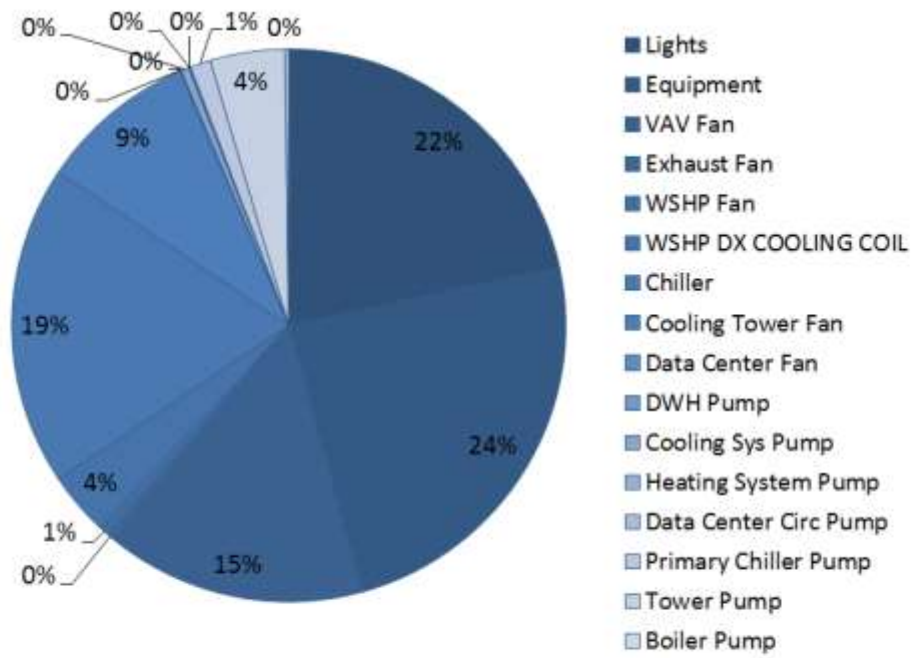




Figure 3.12 Small office with RTU (32% of load is voltage leading and 68% is voltage lagging)



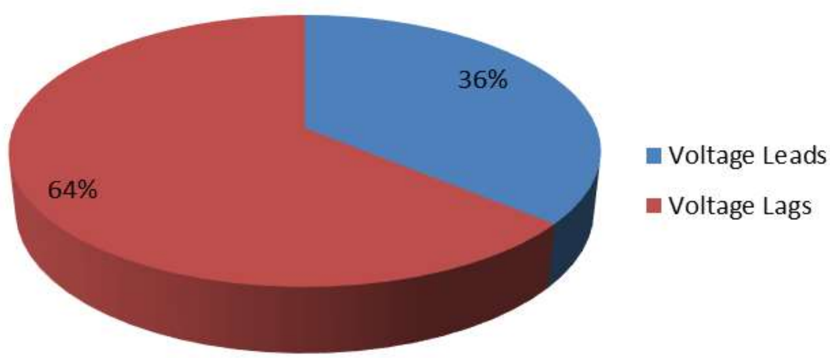




Figure 3.13 Large office with chiller (in 50% of load voltage leads and in 50% voltage lags)

Next, the power consumption of the prototype small office with heat pump is evaluated in extreme and typical weather months in one year. As shown in Figure 3.14, load is categorized as voltage leading and voltage lagging. Results indicate that most of the summer peaks are actually because of voltage lagging loads which do not respond well to voltage control signals. Therefore, methods such as CVR are not relevant to reduce peaks in a building with heat pump during summer. Field studies also show that in regions with high concentration of heat pumps, CVR methods do not yield to the desired power reduction objectives (PNNL Northwest Demo Ongoing Project).

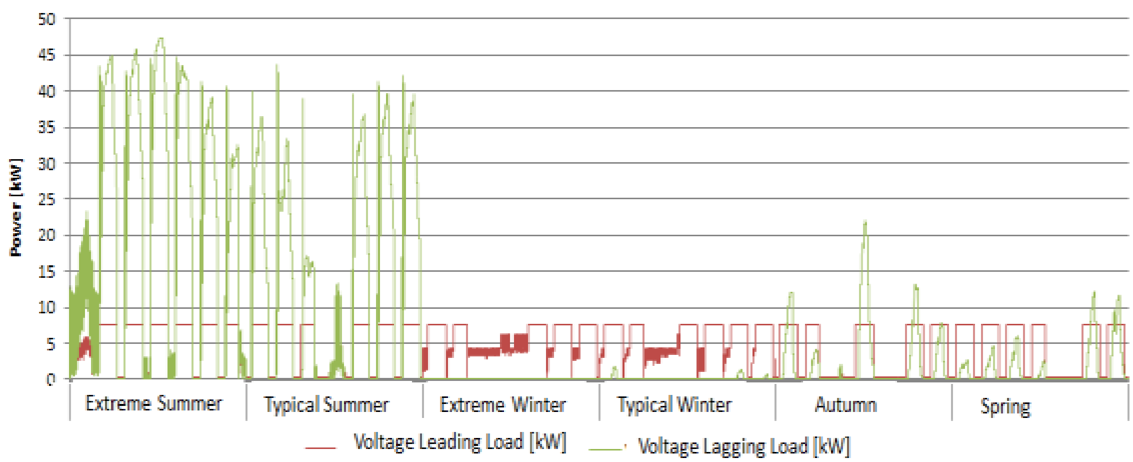



Figure 3.14 Power consumption of prototype small office during different months. Load is categorized as voltage leading and voltage lagging (electric equipment not included).

However, in winter time, some load curtailment can be achieved using CVR. Similarly, other scenarios can be defined to evaluate the potential of voltage toggling for DSM. These scenarios can be used to give recommendations about most effective methods to reduce peak load. For example, a group of commercial buildings can be modelled with different sizes and system types to evaluate the potential in a community of buildings (e.g., university campus) for CVR. Such scenarios support facility managers with decision making in regard to energy efficient operation of their buildings.

## 3.7 Conclusion

This chapter argues that the electrical energy and power performance of buildings should be evaluated in addition to their thermal energy. The major objective of this study is to look into impact of voltage variations on instantaneous power performance of different HVAC components or systems. To achieve that, ZIP models are derived to model voltage based power of AHU fan and RTU. Models constructed were used in conjunction with EnergyPlus models to model both electrical and thermal energy of an AHU fan. Results indicate that the MSE of power estimated (using the method introduced in this work) is lower that power simulated when compared with metered (i.e., measured) power.

Results discussed here illustrate the significance of considering building electrical energy modelling in addition to thermal energy. Thermal-electrical models support different studies such as evaluating power efficiency of building systems in terms of both active and reactive powers, understanding power and energy reduction methods such as CVR. In the last section, load categories (voltage leading or lagging) in different building types were assessed to show how electrical characteristics (e.g., voltage) can support building-grid related studies.

# 4. UNDERSTANDING POWER DEMAND OF AIR DISTRIBUTION SYSTEM FROM A PERFORMANCE PERSPECTIVE

*After having been involved in numerous modeling and simulation efforts, which produced far less than the desired results, the nagging question becomes; why? … the answer lies in two areas. First, we must admit that we simply don't understand. And, second, we must pursue understanding. Not answers but understanding.*

*Gene Bellinger*

## 4.1 Introduction

This chapter aims to pursue better understanding of building systems with respect to the electricity system. This is achieved through elucidating the underlying principles of a power performance framework that identifies how building systems respond to certain "power" performance criteria and develop a set of performance indicators to measure power performance of building systems in conjunction with their control strategies. Through structuring this framework, a recipe is developed for determining relationships and interactions that can be discerned from, and applied to power performance assessment and rating of all types of energy systems that intend to enhance power resiliency in addition to energy efficiency and sustainability. In other words, both buildings and the power grid will benefit from this work and the performance framework that emerges. By understanding building systems as the end nodes (i.e., demand side) in the power supply system, we want to investigate how they can support the management and operation of the modern grid while considering the trade-off between energy efficiency and services provided to the grid. The latter has become critical in recent years because of the increasing diversity and variability of loads (Bollen, 2000 and Jouanne & Banerjee, 2001) and the growing penetration of intermittent renewable generation sources, both of which are contributing to volatility in the power system. The volatility caused is forcing utilities to run closer to the operating limits of their generation systems, which is not ideal (NEMA, 2014), or to make additional investments in the power system capacity (power generation) and infrastructure (transmission, and distribution). With an ever-increasing demand for power resiliency, buildings are evolving from being merely consumers of electricity to power generators and transactors. This research will ultimately support decisions related to performance-based control and operation of buildings as active participants in the power system that contribute to power resiliency as much as global energy efficiency and sustainability. In doing so we aim to support the trade-off decisions between energy efficiency and investments in power management at the building site.

The approach adopted here is based on the contemporary methodology for performance measurement and assessment. Following the engineering perspective and approach adopted for performance based building design and operation, the objectives of this chapter can be achieved by identifying systems and interactions within and between them that determine how a set of functions that we define at the outset is achieved. The level at which these functions are achieved is usually expressed as a set of criteria that are quantifiable. In our case this boils down to defining the criteria by which we express these requirements and then measure (through real or virtual experiments) how well the expected functions are achieved or fulfilled. The new criterion or multiple criteria that we intend to define are chosen such that they collectively define “power performance”. The next step is then to formulate quantifiable performance indicators and their measurement methods that express how well a defined function is achieved. This process conforms to a conceptual framework that systematically situates power demand and capacity in the context of building performance assessment.

This effort will assist and support facility managers, building owners, researchers, and engineers to understand the underlying mechanisms, interactions, and elements that affect power performance of buildings’ systems known as energy systems in the power grid. The significance of understanding instantaneous power behavior of buildings can be revealed in its applications in decision support systems for facility management. It should be well understood that most criteria can only be measured under given scenarios of use. We need to study the complete system under one or more fixed scenarios that are deemed significant for the study of performance. The scenarios thus serve as a controlled experiment under which we study performance. The implication is that if a certain system and control design shows higher performance than another design, under the same fixed scenario, it is deemed as higher performing.

Load forecasting is a critical element in decision support systems related to power efficient operation of buildings in the grid. Most facilities lack historical data that show how much power or energy can be reduced by implementing certain advanced control strategies. Without such data, we cannot predict and forecast the load profile of a building in presence of power management techniques. We propose to generate this information through appropriate prediction methods, e.g., simulation to be used in forecasting models.

The next sections present details of the methodology used to look into a building system from perspective of a variety of disciplines involved in design, installation, and operation of these systems. Understanding the physics of a problem and different aspects of the systems associated with it are the first steps towards characterizing the inter-relationship among elements and key parameters that can be used to describe a the behavioral aspects of that system and to derive simplified performance measurement methods, i.e. conducting controlled experiments in fully prescribed conditions.

## 4.2 Methodology

In the realm of high performance building design and operation, different stakeholders define and negotiate performance requirements and how to satisfy them. This involves an agreement on how to choose the right measurement methods to enable quantification of performance criteria for objectives/functions they have defined. According to Augenbroe (2011), "a rigorous, system-theoretic definition of performance indicators is necessary to prepare a rational decision process." In general, the key characteristics of performance-based design and operation are the explicit formulation and definition of performance requirements according to 'functions' in order to guide decisions and, to evaluate these using the right set of criteria with specific metrics attached to guarantee fulfillment of these requirements. As the old management adage says: "you can't manage what you can't measure." Measurement methods illustrate relationship between parameters and interaction among systems. They also support defining requirements in addition to quantifying performance criteria.

As it was mentioned earlier, the objectives of this chapter are pursued by applying an engineering perspective on performance based building design and operation. It should be noted that in engineering and manufacturing, a performance approach is mainly applied to facilitate the 'design' process. Decision science and value-focused thinking in engineering e.g., Hazelrigg (2012) and performance based building in architecture, e.g., Augenbroe (2011), have been established around the 'effective[1] design of an artifact.' However, the work presented here is more concerned with performance-based operation of a building while concepts can be applied during building design process as well.

In both design and operation process, expectations of clients, building owners and occupants can be expressed in form of performance requirements. This requires careful formulation of statements of performance requirements and effective management of a well-defined and tested procedure that enables and assures their fulfillment. The main goal of designers and facility managers is to fulfill requirements of their clients. This is not a straightforward task and difficult, if possible at all, to accomplish without a systematic framework for the definition of performance measures and quantification methods. The dialogue among different stakeholders will lack continuity and rationality without establishing such systematic approach. This systematic procedure and framework toward performance assessment is critical to satisfy expectations of the client. It has been well understood that "a performance based approach is a key enabler of rational decision-making across many stakeholders and based on a large set of performance criteria"

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[1] Merriam-Webster defines *Effective* as "producing a decided, decisive, or desired effect" (Merriam-Webster, 2004).

(Augenbroe, 2011). Quantification of these performance criteria identified (through simulation experiments or other proper methods) is the only way to have a consistent and apple to apple metric to inform decisions.

Augenbroe (2011) defined a compulsory performance based framework and a systematic approach to structure it. This performance approach offers a step-by-step method to design an application or case specific performance tree for categorization of functionality and their mapping into sets of performance criteria with well-defined measures. In the context of building design or operation, the high level steps in this process are: 1) agreement on performance criteria to satisfy functions identified, 2) agreement about ways to quantify them in order to quantify required and fulfilled levels of performance, and 3) making rational multi-objective design or operation decisions considering preferences of the client, occupant, or building's owner.

Therefore, to evaluate performance of an emerging concept (e.g., new design or operation strategy), in this case evaluation and ultimately rating of building systems power performance, it is critical to first categorize building functions to enable mapping of those onto a set of performance criteria that can be used to quantify building performance in terms of power and capacity efficiency. To define quantifiable expressions of performance to objectively compare and evaluate design and operation alternatives, the initial task is to decompose the main function into smaller manageable functional units, and the technical system into smaller manageable technical systems. The knowledge of the system level characteristics and interactions can then be utilized to formulate methods to quantify performance indicators found. By performing the top-down functional decomposition and bottom-up technical system aggregation approach (shown in Figure 4.1), one will arrive at functional criteria that can be expressed as explicit performance requirements. The reason for performance requirement specification, rather than prescription of properties, is to ensure that a building system is capable of fulfilling the functional requirements at a defined level of performance (Augenbroe, 2011).

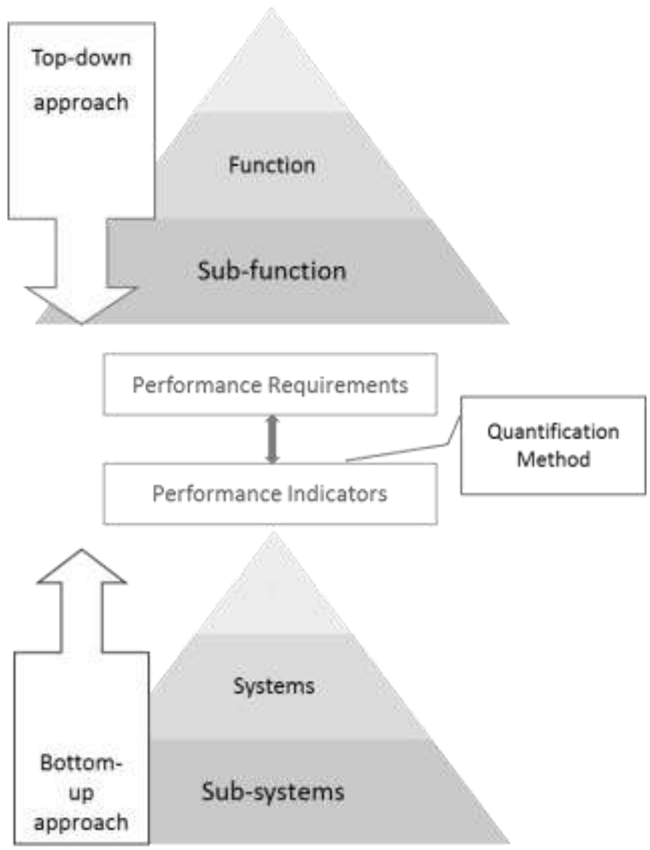



Figure 4.1 Top-down functional decomposition and bottom-up technical system aggregation approach to capture quantifiable performance indicators

This chapter explores performance requirements of building systems as sub-systems of the power grid through identification of performance criteria in this domain, and proposes metrics that can be used to quantify the criteria-associated performance indicators. This cannot be achieved without first identifying a functional hierarchy and classifying building systems and sub-systems that contribute to satisfying these functions. Figure 4.18 provides a detail model of the top-down and bottom-up performance approach explained. Although this framework is generic at the top level (i.e., functional hierarchy), it is constructed to show how building power (i.e., electric energy) performance can be quantified. Therefore, only those properties of the building and its systems that determine power behavior need to be considered in the formulation of performance criteria and PIs. Consequently, in the bottom half, systems, sub-systems, and their components are specifically discussed in terms of their power characteristics. Because of the complexity and scale of the problem, this performance framework is for now defined for a specific building case and focuses on one building system, the air handling unit (AHU). All relationships of a centrifugal supply fan element in the AHU system influencing power behavior of the building energy systems in the grid are classified and described.

The following sections describe different layers of this framework in this order:

1. Identification of functional requirements.
2. Classification of systems and elements that play a role in achieving the functions identified.
3. Formulation of statements (criteria) of performance requirements and PI names/descriptions.
4. Discussion of quantification method for each criterion, leading to PI valuation.

### 4.3 Function Identification and Performance Requirements

Traditionally, building primary functions were formalized and understood according to qualitative user ‘expectations.’ The ‘user’ (i.e., stakeholder) class or type defines the scope for formulation of a performance framework. The direct 'user' of a building are its occupant(s) organization but there are other stakeholders impacted by how a building performs as a result of its design, construction, and operation. Example of these are the building owner and the society as shown in Figure 4.2. In this model, it is assumed that other stakeholders involved, such as designers, builders or contractors, facility managers, and the local and federal government intend to support and satisfy expectations of impacted parties (occupants, owner, and the society) during the life-cycle of a building.

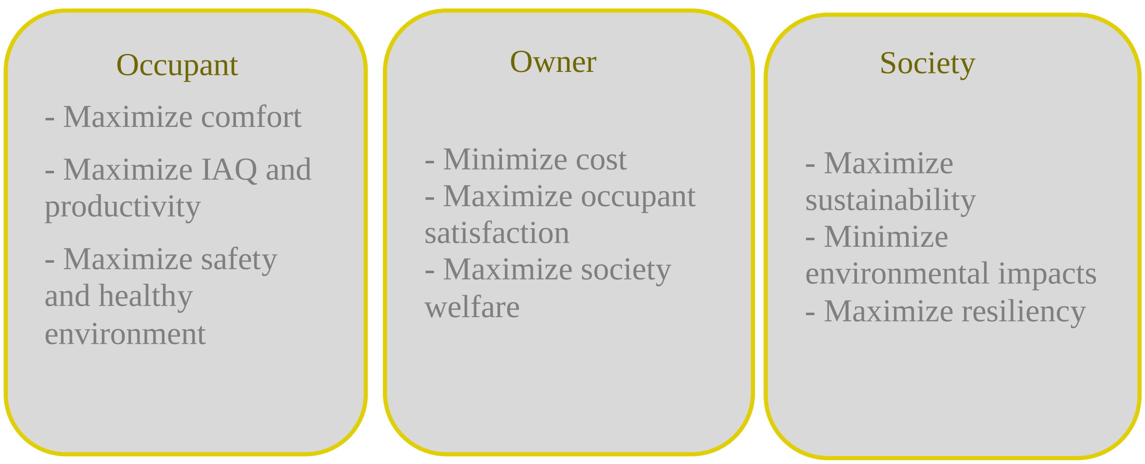



Figure 4.2 Performance scope based on qualitative expectations of different stakeholders regarding building performance.

As shown in Figure 4.2, different parties involved have different expectations which are reflected in how they want a building to perform. For instance, following the main function of a building, which is providing shelter and satisfying the main activity and service of the building (e.g., school, hospital, office, etc.), occupants expect a building to be a comfortable, safe (including structural safety, fire safety, accident safety, and security) and healthy (characterized by indoor air quality, moisture and mold safety, acoustics, visual comfort, hygiene, and water quality) environment (Becker, 2008). Satisfying these functions at a sufficient level of achievement would ensure the occupant's well-being and productivity. "When the design of a facility satisfies the emotional, cognitive, and cultural needs of the people who use it and the technical requisites of the programs it houses, the project is functionally successful" (Todd & Fowler, 2010). Yet, the building owner expects the building to satisfy occupants' expectations while minimizing operating cost and environmental impacts. The society and the government also expect the built environment to have high performance design and be operated considering current global concerns such as sustainability, climate change, and power resiliency.

To assess performance of buildings in the power system, we are actually evaluating building systems in the context of one of the larger energy systems, which is the electricity system. Until today, buildings and the power grid have been designed and operated independent of the performance concerns of the other. The main function of the building has been to provide a comfortable shelter while the electricity system was expected to provide service to buildings. The main performance criteria of the power grid have traditionally been stability, reliability, and affordability. However, the power grid is evolving and going through major changes to satisfy the requirements of the modern grid. Today, the grid has further performance requirements. It should be sustainable (i.e., energy efficient) and even more reliable (i.e., resilient) in addition to its traditional objectives. This is one of the main reasons behind the need for building-grid integrated assessment and the need for buildings to provide ancillary services to the power system. Therefore, it is important to consider functions and performance considerations of the power grid although the main objective of this study is to formulate a framework for performance assessment of ‘buildings’ in the context of the modern grid. By considering certain performance requirements of the power system, we ensure development of methods and techniques that support rational decision making about the design and operation of buildings because they enable quantification of the trade-offs between building energy efficiency and investments in power management at the building site.

Following the general discussion about building functions and the grid requirements, the top section of the performance framework is defined using the top-down functional decomposition method. The top layers of this performance framework as shown in Figure 4.3 are strictly selected based on the scope of this work and they do not represent the broader performance requirements traditionally considered in building design such as IAQ and safety.

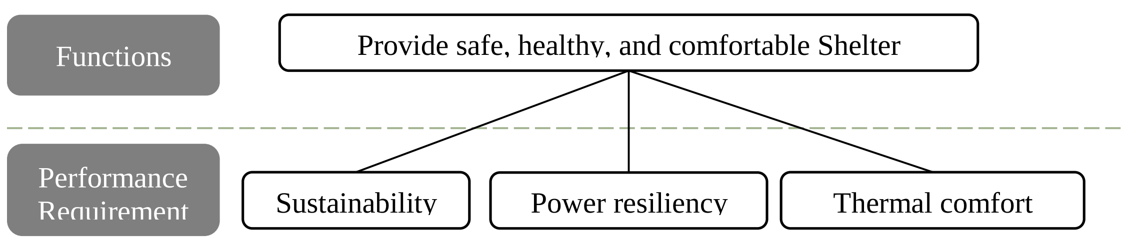



Figure 4.3 The top layers of the top-down functional decomposition of the performance framework.

Performance requirements of sustainability, power resiliency and thermal comfort are those that will be considered in definition and formulation of performance indicators that support rating a building in terms of power efficiency. Performance criteria and indicators will be introduced after a comprehensive discussion about building systems and sub-systems that support achieving high performance buildings in terms of power and service they can provide to the grid to fulfill requirements of the power system.

## 4.4 Classification of Systems and Elements

The second half of performance approach, the bottom-up assembly of building systems, involves definition of building systems, sub-systems, elements, their relationships, interactions, and constraints that are employed to fulfill building functions while addressing performance requirements. These are first identified and discussed in this section; their relationships are then presented in the performance framework.

The technical systems that play a role in power performance of buildings are either related to the lighting system or fall under the umbrella of the "HVAC/mechanical system" (more precisely, the electricity consumers of the HVAC system). Lighting system and its control are beyond the scope of this work. It should be noted that research and studies in the areas of DSM have identified HVAC as a flexible load among other building systems (e.g., plug load and lighting) that has potentials for DR, load following, and regulation purposes. This is because of several reasons: 1) HVAC systems consume a large amount of electricity in commercial buildings, 2) the thermal mass of buildings reduce the impact of zone temperature adjustment on occupants thus offering considerable flexibility and elasticity in regard to power demands, and 3) most HVAC systems are controlled automatically using building automation systems (BAS) nowadays, which can be used to implement a variety of advanced control strategies for power reduction (Watson et al., 2006 and Wang et al., 2014).

Because of the complexity of HVAC and different types of systems available, here, the focus is on electricity consumers of the air distribution system (i.e., AHU system). The largest electricity consumer with an electric motor in an AHU is the supply fan. Hence, that is the main component considered in this work for further discussion and analysis. Electric motors consist of a "mechanical drive," "electrical system," and "control system." The properties and interactions among decomposed elements of each of these systems are discussed in detail in the following sections to carefully select the performance indicators that can measure how a system fulfills functions identified.

### 4.4.1 Air Distribution System – Electric Motors

A common HVAC system consists on an indoor air loop, chilled water loop, refrigerant loop, condenser water loop, and outdoor air loop. The indoor air loop includes terminal units, cooling coils, dampers, fans, ducts, and controls. The chilled water loop includes cooling coils, chiller evaporators, pumps, pipes, valves, and controls (ASHRAE, 1997). As it was mentioned earlier, to narrow down the problem, we focus on an AHU system. A performance tree is structured for this system and its performance in terms of some advanced control strategies to reduce power is measured and evaluated in the next chapter.

The basic generic AHU incorporates an outdoor air system and a supply fan (see Figure 4.4). There are also options for night cycle operation, a heat recovery system, an economizer, pre-heat and pre-cool coils and an exhaust fan. Additional components such as heating coils, cooling coils and humidifiers may also be added to generic AHUs. Electricity consumers of an AHU which have impact on power performance are those with motors. The main electricity consumer of an AHU is the supply fan. It is estimated that over 60% of the electrical power generated in the US is used to power fans and pumps (Lönnberg, 2007). Supply fans in AHUs are used here to illustrate how the power performance framework should be approached and structured to rate performance of a system in regard to certain requirements.

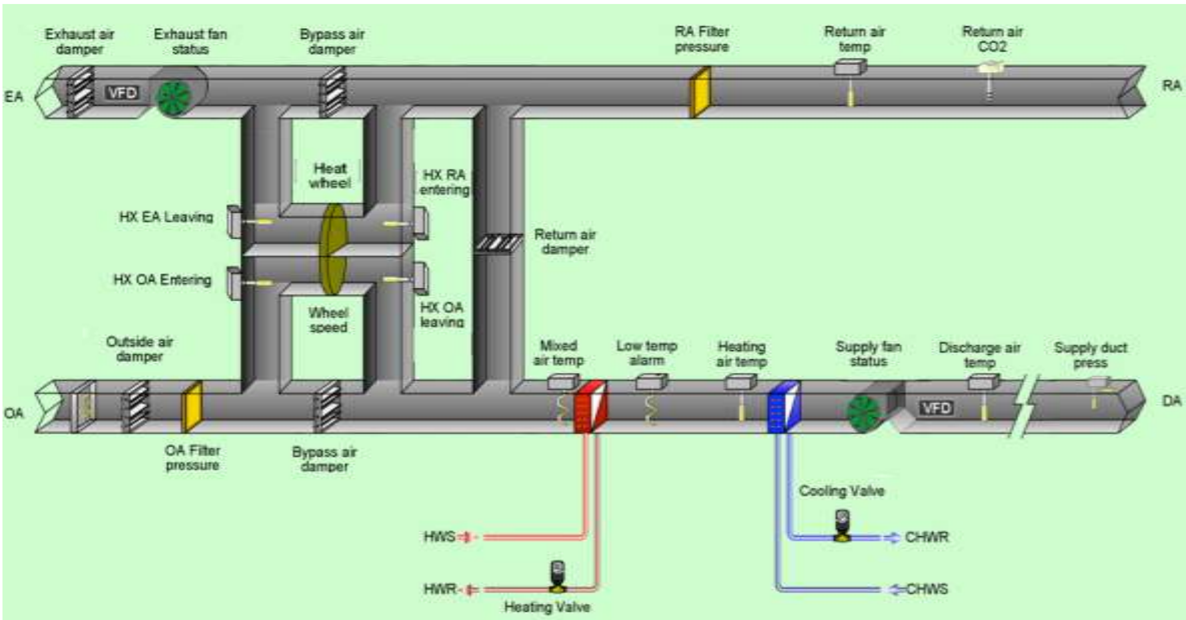



Figure 4.4 Components of an AHU

The purpose of the following sections is to describe systems, components, attributes and parameters that affect power consumption and hence its calculation.

Motor Types

Electric motors can be classified as two groups of alternating current (AC) and direct current (DC). Figure 4.5 shows a detail classification of electric motor types. AC induction (asynchronous) motors are the common electro-mechanical devices and the typical type of motors used in commercial AHU fans. Induction motors, which result in inductive loads in the power system, require a magnetic field to operate. The magnetic field in a coil of wire (i.e., stator) is produced by the reactive power drawn from the electrical energy source. Therefore, in inductive motors, in addition to the real power applied to the shaft to rotate the rotor, reactive power is also drawn from the energy source to produce the magnetic field of stator. Because of the time it takes to develop the magnetic field, current and power lags the voltage applied in such motors.

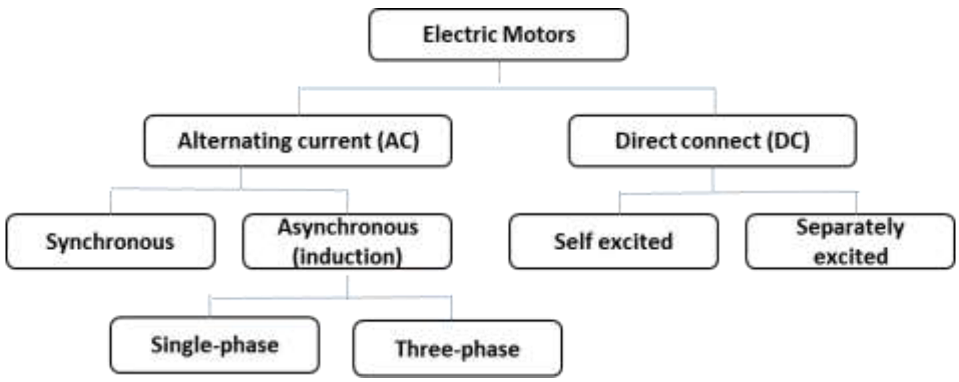



Figure 4.5 Electric motor classification (Sahni et al., 2012)

In an induction motor, the stator consists of poles carrying supply current to produce a rotating magnetic field. The speed of this rotating field is called the synchronous speed and depends on the frequency of the input power and the number of poles. In an asynchronous motor, commonly referred to as an induction motor, the rotor rotates at a speed slower than the rotating magnetic field in the stator. The synchronous speed of an induction motor depends on the frequency of the power supply and on the number of poles for which the motor is wound. The higher the frequency, the faster a motor runs. The more poles the motor has, the slower it runs. The slip method to estimate load is used when only operating speed measurements are available. The difference between the actual rotor or shaft speed[1] and the synchronous speed is known as 'slip'. The actual speed of the motor is less than its synchronous speed. The amount of slip present is proportional to the load imposed upon the motor by the driven equipment as shown in Figure 4.6. For example, a motor running with a 50% load has a slip halfway between the full load and synchronous speeds. The motor load can be estimated with slip measurements as shown in Equation4.1.

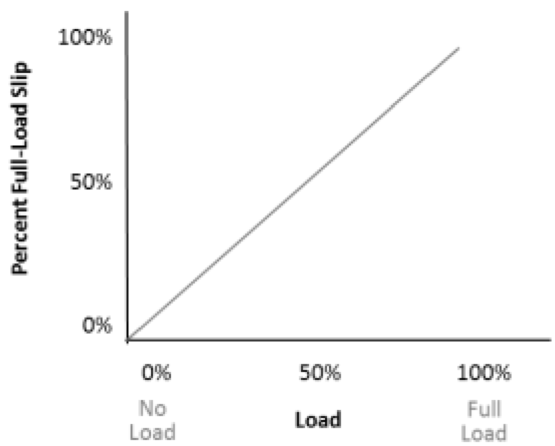



Figure 4.6 Percent motor slip as a function of motor load

$$Load = \frac{Slip}{S_{sync} - S_{nominal}} \qquad 4.1$$

and

$$\text{Slip} = S_{sync} - S_{measured}$$

Where,

$Load$ is the output power as a percentage of rated power

$S_{sync}$ is the synchronous speed

[1] Discussed in the next section.

$S_{nominal}$ is the nameplate full speed

$S_{measured}$ is the measured speed in rpm

In induction motors, high power efficiency has been achieved by controlling the slip speed (Kim et al., 1984 and Kirschen et al., 1987). Power efficiency along with dynamic performance of motors are two measures that have been used to assess performance of induction motors (Kim et al., 1992).

Application of Induction Motors in HVAC Systems

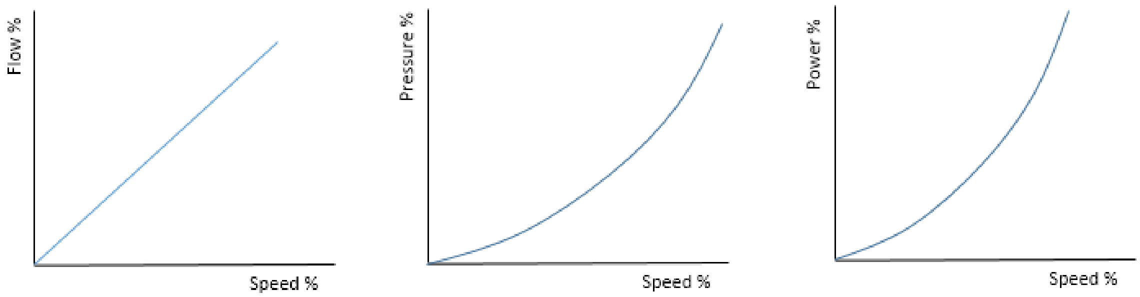
Induction motors are used in variable frequency drive (VFD) and variable speed drive (VSD) systems such as variable torque centrifugal fans, pumps, and compressors. Most motors are designed to operate at a constant speed, however, speed, torque, flow, and subsequently energy consumption in VFD motors can be controlled by altering motor input frequency and voltage (Bonnet and Boteler, 2001; Neuberger and Weston, 2012; Saidur et al., 2012). This is because of emerging requirements of modern life such as concern about energy efficiency.

Centrifugal fans, also known as squirrel cage fans are typically the induction motor type used in commercial AHUs to move the air. These fans could be operated at single speed, different set of speeds, or have variable speed. Different methods are used in VSDs to control speed, which can be categorized as: 1) mechanical, e.g., using belt drivers, 2) hydraulic, and 3) electrical, by having a controller to vary frequency (Saidur, et al., 2012). If speed is controlled by electrical means, the VSD is normally referred to as VFD. There are also adjustable speed drive (ASD) device. If both electrical and mechanical means are used to control the motor speed, the device is known as ASD (Saidur, et al., 2012).

### 4.4.2 Mechanical Drive and Characteristics

The mechanical drive of an induction motor responsible for transmitting torque and rotation to the rotor is called a 'shaft.' The shaft speed affects performance and overall behavior of a motor according to affinity laws described below. Speed is measured with a unit of revolutions per minute (rpm) and in VFD drives, it is impacted by several parameters, such as slip factor, the input power frequency, and the number of electrical magnetic poles at which the motor is wound. The higher the frequency, the faster the motor runs. The more poles the motor has, the slower it runs i.e., mechanical speed = electrical frequency/ the number of poles.

Most fans and pumps are of the centrifugal design type. Centrifugal fans and pumps follow the affinity laws of pressure, flow and power consumed. Therefore, it is important to understand affinity laws to capture the relationship between these parameters and how they affect operation of fans. For centrifugal motors, the affinity laws can determine the system performance. According to affinity laws (Figure 4.7), with impeller diameter held constant: 1) flow is proportional to shaft speed having a linear relationship, 2) pressure is proportional to the square of shaft speed, and 3) power is proportional to the cube of shaft speed. These set of laws are important for understanding how to design effective control strategies. Energy savings of VFDs can be calculated using affinity laws. For example reducing speed by 30% results in flow reduction by 30%, but power will be reduced by about 60%.




$$\frac{Flow_1}{Flow_2} = \frac{RPM_1}{RPM_2} \qquad \frac{Pressure_1}{Pressure_2} = \left(\frac{RPM_1}{RPM_2}\right)^2 \qquad \frac{Power_1}{Power_2} = \left(\frac{RPM_1}{RPM_2}\right)^3$$

Figure 4.7 Affinity laws with constant impeller diameter

Another method used to increase performance of centrifugal fans is changing impeller diameter. Tipping and trimming are two methods used to achieve this in the field instead of purchasing a new motor (Chunxi et al., 2011). To explain the impact of impeller diameter, trimming laws are deduced from the affinity laws to predict performance of the system after trimming or enlarging the impeller diameter. According to these laws: 1) change in impeller diameter is proportional to the change in flow, 2) change in pressure is proportional to the square of change in impeller diameter, and 3) change in power is proportional to the cube of impeller diameter (Chunxi et al., 2011).

In general, large high speed motors have the best efficiency (Bonnet, 1993). However, it should be noted that if a motor is not operated at full load capacity, it will result in low power factor (Bonnet, 1993).

The power consumption of variable speed drive (VSD) fans can also be described by fluid dynamics. Power is influenced by two parameters, which are mass flow rates of fluids through the fan and the pressure difference between the inlet and outlet of the fan (Lu et al., 2005).

$$P_{fan} = \frac{m_{SA} \cdot H_{SA}}{g_c\ \eta_{SA}} \qquad 4.2$$

Where, $m_{SA}$ is air flow rate of supply air, $H_{SA}$ is air pressure provided by the fan, $\eta_{SA}$ is efficiency of supply air fan, $g_c$ is a constant, and $\eta_{SA} = f\ (m_{SA}\ , H_{SA})$. Equation 1 describes power as a function of mass flow rate and air pressure. Total efficiencies of fans can be expressed as polynomials, neural networks, or other curve fitting methods (Lu et al., 2005).

Another important parameter to mention is torque. Some systems may run at constant torque. In case of air handling unit, if the requirement is to maintain a constant static pressure at discharge, then the control system should keep a constant torque input. In such case, torque follows the second affinity law and varies with the square of speed, similar as pressure. In this work, because the focus is on AHU, we assume torque to remain constant in order to maintain constant pressure.

### 4.4.3 Control Systems

There are a variety of control strategies that can be applied for load and energy management. Some of these strategies are discussed in detail in the next chapter and their performance are evaluated in simulation environment. Watson et al., (2006), Smith et al. (2010), Escrivá-Escrivá et al. (2010), Kosek et al. (2013), Ma et al. (2014), Riker et al. (2014), Wang et al. (2014), Olivieri et al. (2015) are examples of work related to control strategies to achieve DSM e.g., peak clipping, valley filling, or load shifting introduce by Gellings (1985). These are commonly known as DR control strategies and some overlap with what is known as advanced control strategies such as global optimization (Lu et al., 2005), improved scheduling and operation of HVAC systems without sacrificing the occupant comfort (Serra et al., 2014), outdoor air economizer cycle, programmed start/stop lead time, load reset and occupied time adaptive control strategy (Huang et al., 2006). These strategies can be initiated automatically using the building automation system (BAS) or manually by the facility managers on-site.

In addition to understanding and evaluating DR or advanced control strategies, it is also important to evaluate performance of the 'controller' itself in regard to DSM. This is because while methods such as global and local setpoint adjustment are effective in reducing energy, they are not as favorable for some emergency level of DR and for some ancillary services e.g., frequency regulations. This is because some conventional control strategies such as setpoint adjustment have inherent delays in responding to DR control signal. Therefore, they cannot fulfill requirements of the grid real time operation by responding in timely manner (Xue et al., 2015; Antonopoulos and Koronaki, 2000; Kueck et al., 2009). As a result, it is important to look into different elements of the control system to understand how well and effective it can satisfy the control objective.

"HVAC control problems are not trivial" (Underwood, 1999). Good HVAC control systems have historically been designed to provide comfort at minimum energy use, operating cost and initial cost (Underwood, 1999). Current HVAC controllers, energy management control systems (EMCS), and building automation systems (BAS) are built to reduce cost, increase energy efficiency, and improve performance. Control functions of a BAS can be categorized as local and supervisory. Wang and Ma (2008) have classified control functions as illustrated in Figure 4.8 below.

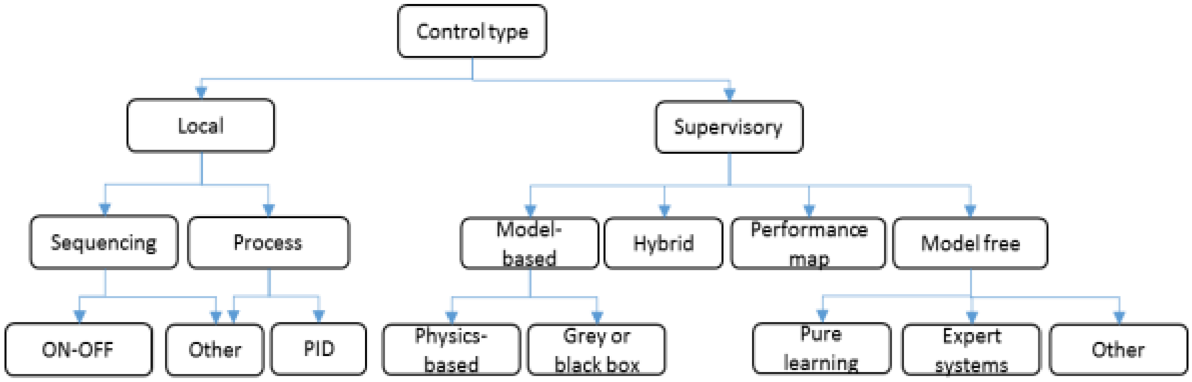



Figure 4.8 Classification of control functions (Wang and Ma, 2008)

Local control has been the predominant control type in the history of HVAC control and most studies have focused on local control e.g., Moore and Fisher (2003), Engdahl & Johansson (2004), Zhang et al. (2005) and etc. Controller types used in HVAC local control loops include on/off control, step control, modulating control, proportional-integral-derivative (PID), and proportional-integral (PI) control. PI was the most common and widely used control method in practical HVAC systems until recently (Mehta, 1984). In practice, a proportional only controller can result in fast response with an *offset*. When the integral control mode is combined with the proportional mode, it resolves the *offset* issue –a sustained error at steady-state conditions (Underwood, 1999). The gain and response have proportional relationship and the higher the gain, the faster the response of the control system. However, a high gain also results in overshoot or an indefinite cycling of the system. Hence, research in this area supports achieving quick response by means of adding or preserving the proportional part in the control model rather than increasing gain (Huang et al., 2006). A PI control can result in relatively good performance in terms of system response, stability, energy consumption and thermal comfort, however, it is difficult to select effective proportional and integral gains for multiple control loops.

Today, the typical local process control used in the HVAC is proportional-integral-derivative (PID) control (Wang and Ma, 2008). By adding a derivative term to the PI controller, we achieve a three-term proportional plus integral plus derivative controller. The purpose of the derivative is that it results in faster response to sudden error changes. However, it does not act upon very slow changes in error. Therefore, it just compensates for the slowness in response resulting from integral action (Underwood, 1999). Figure 4.9 depicts typical local process controller responses to a step change.

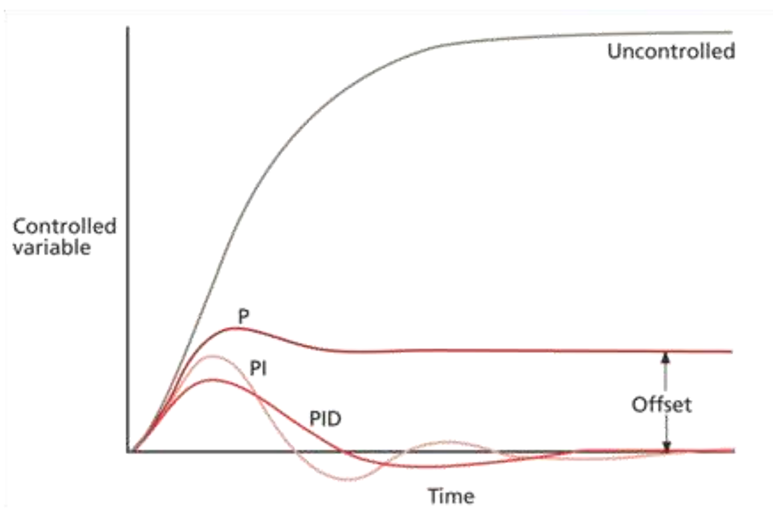



Figure 4.9 Typical controller responses to a step change.

Supervisory control has been growing in the field of HVAC control with the increasing number of buildings equipped with BAS. Supervisory control works by systematically finding the optimal operating conditions for the overall system and considers interactions among all components and their associated variables. The optimum is defined as minimizing energy input or operating cost to maintain zone temperature at occupant comfort level. In supervisory control minimizing operation cost is not necessarily equal to reducing system energy input (Wang and Ma, 2008). One of the advanced supervisory control methods that has been used in industry since the 1980's for process control is model predictive control (MPC). In buildings, MPC-based methods are used in more complex plants to optimize HVAC operation. In MPC, models are used to predict the behavior of the controlled system and its response to changes in control signal (e.g., setpoint) over a preceding horizon (Henze and Neumann, 2009; Wallace et al., 2012; Ma et al., 2014). MPC does not replace the local controller, it just optimizes operation based on the objective function embedded and generates setpoint for the lower control loop such as PI or PID.

With an increase in the number of renewable generators with intermittent power generation, the concept of energy efficiency is evolving towards energy flexibility. While buildings should still be designed for energy efficiency, their control and operation should be in line with global concerns which are power resiliency in addition to sustainability.

For the same reason, in the past recent years, the focus of some efforts have shifted to developing control schemes for buildings to support stability of the power grid through deployment of building systems (Lu, 2012, Xue et al., 2015; Cue et al., 2015; Hao et al., 2012 ). The objective of such controllers is to achieve fast system response to DR signal for DSM (Cue et al., 2015), load balancing (Lu, 2012), and frequency regulations (Hao et al., 2012). 'Fast' in such applications is defined as system response within a minute. Lu (2012) discussed possibility of using a forecaster in the controller to proactively determine the zone temperature and status of HVAC in the next time step to be able to adjust the control signal before reaching that time step. Cue et al. (2015) developed and evaluated a fast power demand response strategy using a combination of building passive and active PCM cold storages. Ma et al. (2014) illustrated effectiveness of using an economic MPC for energy and demand minimization in commercial buildings.

Regarding performance of controllers, it should also be mentioned that the sensitivity of most HVAC processes changes with variations in air temperature, water temperature, air volume, and other environmental conditions. Hence, HVAC control loops need seasonal re-calibration or tuning to maintain a steady, stable response. Also, a fine tuned control system may require constant updating against uncertain changes in the system due to strong interactions among different loops. Therefore, development of simple control algorithms that can easily be implemented has been expressed on. This becomes more important when it comes to load management and power control (rather than energy efficiency) because of the faster system response required. Adaptive control algorithms are example of controllers that have shown to have more rapid response, can be easily tuned, have closed loop stability, and acceptable performance in regard to process disturbances and dynamics (Huang et al., 2006).

#### 4.4.4 Constraints

A major constraint to consider is system (i.e., motor) health and safety. Control strategies such as duty cycle or voltage variations should be applied considering operation limits and boundary condition of motors. Constraints related to AHU control can be extracted from constraints defined for global optimization of overall system. These constraints involve physical limitations of components and interaction between components. Physical constraints in AHU control can be related to: temperatures of the inlet and outlet, flow rates, pressure provided by the fans, and the mass flow rate of supply air to each terminal. Constraints related to 'interactions' between components include those described by affinity laws and impact of fan speed or size of impeller on flow rate, pressure, and power of fans (Lu et al., 2005).

### 4.4.5 The Bottom Half of the Performance Framework

After understanding the characteristics, attributes, and parameters of the AHU as discussed above, it is now possible to identify the systems, components and relationships in the bottom half of the performance framework. Here, the bottom half of the performance framework is first broken down into three categories of sub-systems and components according to performance requirements identified. These three categories are: 1) attributes affecting fan electric power consumption and hence performance criterion of power resiliency, 2) attributes impacting energy consumption and hence performance criterion of sustainability, and 3) attributes influencing indoor air temperature and hence thermal comfort criterion. These three categories of elements, attributes, and characteristics have inter-relationships influencing the resulting power behavior in linear and non-linear ways. It should be well understood that power performance can only be defined at the whole system level where the combined effect of all attributes of a given system lead to certain power behavior that can be post-processed to a PI for power performance of the whole system. We will first discuss them as independent from each other to have a clear definition of power, energy, and temperature.

Figure 4.10 depicts the lower half of the performance framework concerned with electric power consumption of supply fan in an air distribution system, i.e., AHU as derived by the mechanical and electrical elements and attributes of the system. This is categorized as the 'electrical and mechanical system.' Fan electric power consumption depends on: 1) fan air power, which is a function of the airflow and pressure difference across the fan, 2) mechanical efficiencies, including fan and belt characteristics, 3) and electrical efficiencies consisting of motor and drive properties electrical characteristics e.g., voltage and current (DOE, 2016). In general, fan power can be calculated in different ways and as a function of different parameters, such as:

1) Power = $f$ (slip, synchronous speed, measured speed)
2) Power = $f$ (shaft speed) and Shaft speed = $f$ (flow rate, pressure, fan efficiency)
3) Power = $f$ (impeller diameter) and Impeller diameter = $f$ (flow rate, pressure)
4) Power = $f$ (voltage, current, frequency)

It should be noted that for systems with variable flows, most of these parameters are not constant and all are interrelated.

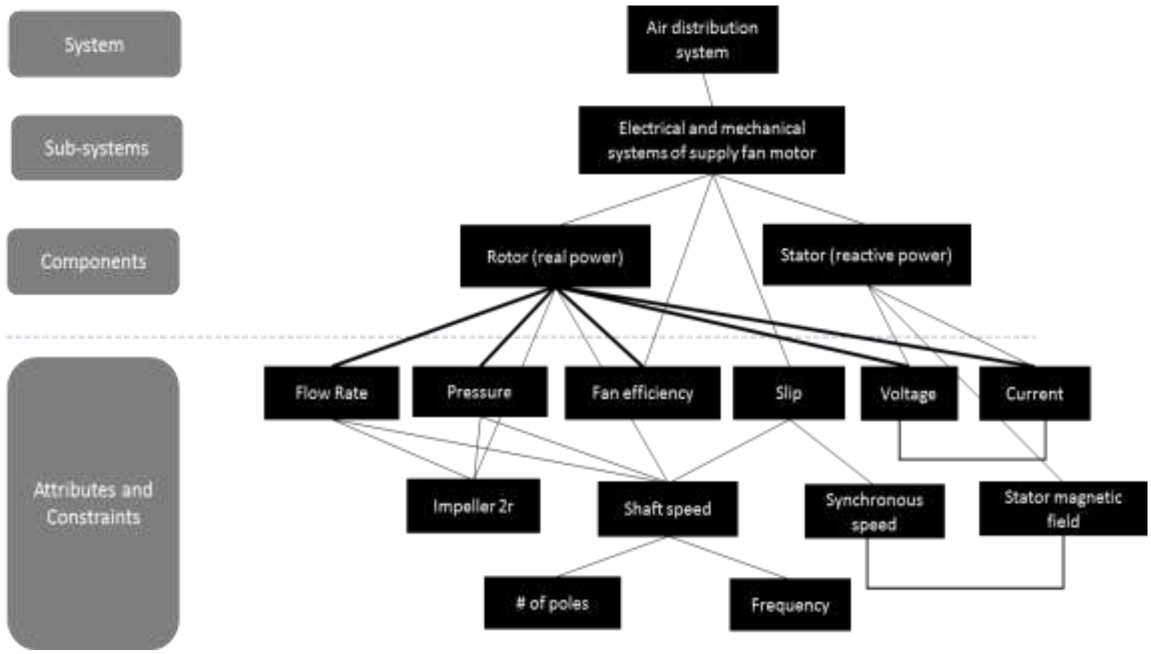



Figure 4.10 The bottom half of the performance framework representing mechanical and electrical elements and attributes affecting power consumption of supply fan in an air distribution system.

The bottom half of the performance framework also contains the 'thermal system' beside the mechanical and electrical system described and depicted in Figure 4.10. This thermal module is defined by building characteristics such as window and wall types, material, and building layout. These building characteristics affect building energy demand (i.e., zone thermal load) calculations. The cooling or heating load of a thermal zone is defined as the rate at which heat must be removed or added to a space to maintain a constant temperature. The standard method used for calculating zone loads is the heat balance method using conduction, convection, and radiation as discussed in section 2.2 under Building Energy Modeling. Variations in zone load resulted by changes in building envelope and layout affect energy performance, air flow rate and subsequently the power consumption of the AHU fan. This thermal module of the performance framework in illustrated in Figure 4.11.

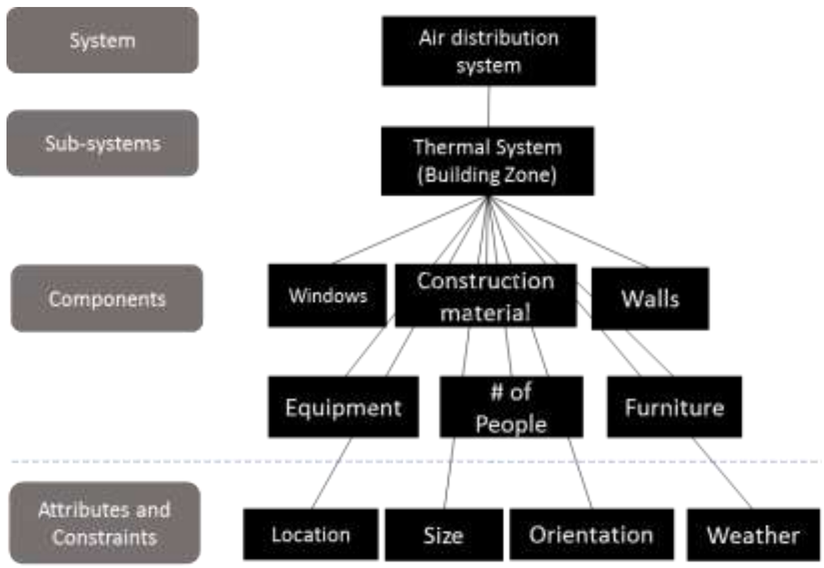



Figure 4.11 Thermal system components, attributes and constraints

The third system or sub-system of the air distribution system is the ‘control system.’ Control systems were discussed in detail in section 4.4.3. Beside the type of the controller and functions used, there are three basic elements in any basic or complex HVAC control system. These are the sensor, controller (including the actuator), and the controlled device. As the control look shown in Figure 4.12 indicate, sensors measure the actual and current value of controlled variable such as temperature, humidity or flow and provide this information to the controller encompassing the control function and logic. A controller receives input from the sensor(s), processes the input based on its logic and then produces intelligent output signal for controlled device. For instance, if zone temperature is larger than the setpoint and the system is in cooling mode, it sends control signal to the controlled device (e.g., the fan or valve). Then the controlled device takes action to adjust the controlled variable (e.g., temperature) as instructed by the controller. Figure 4.13 illustrates the control system of the air distribution system as described for the bottom half of the performance framework.

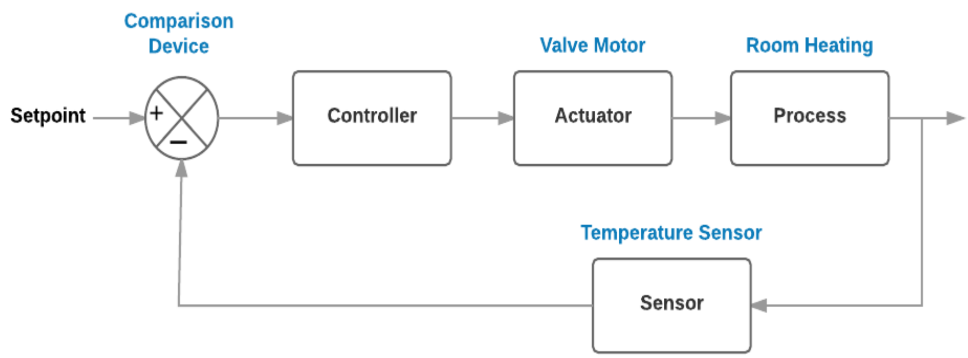



Figure 4.12 Simple diagram of AHU control loop.

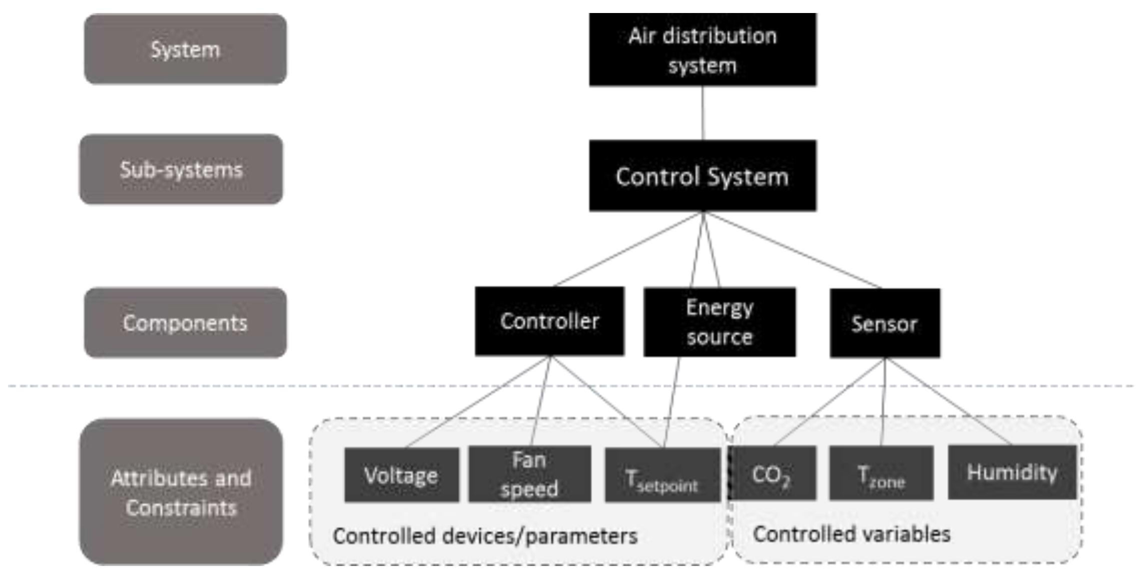



Figure 4.13 Control system components, attributes and constraints.

The forth system in the bottom half of the performance framework is the 'occupant behavioral system.' This system involve parameters, elements, and attributes affecting human sensation of thermal comfort. Occupant thermal comfort and assumptions undertaken in this work will be further discussed in Section 4.5.3Thermal Comfort In short, there are other internal, external, and psychological factors and elements affecting thermal comfort of occupants in a building beside indoor air temperature. These include outdoor air temperature, mean radiant temperature, air movement, relative humidity, clothing, activity levels, individuals' metabolic rate and their internal core temperature, in addition to psychological aspects. Although these are important factors, they are not considered in this work because a lot of assumptions should have been taken into account to estimate them making it difficult to have reliable results. Hence, thermal comfort is only derived as a function of indoor air temperature and thermostat setpoint.

## 4.5 Performance Criteria and Quantifiable Performance Indicators

The previous section elaborated on the top and bottom parts of the top-down functional decomposition and bottom-up technical system aggregation approach used to define a performance framework. Up to here, we identified, classified, and formulated: 1) functional requirements of the building in relation to the power grid and 2) systems that support intended functions. Now, we should transform these into performance criteria and quantitative PIs. The discussions in the previous sections regarding identification of functions and classification of systems lead us to identification of performance criteria or in other words formulation of statements of performance requirements. The selected performance criteria are derived from those higher level objectives of the energy system (more specifically, the electricity system) that are defined here as power performance requirements of buildings. These performance criteria can be supported by efficient design and flexible operation of buildings and facilities. These performance criteria are defined, measured, and assessed based on buildings functions and building simulation engines have been developed in order to generate results that support related decisions. According to Augenbroe (2011), the performance criterion under study is at the heart of the experimental set-up. Therefore, this section covers the middle part of the top-down functional decomposition and bottom-up assembly of building systems approach, where 'functions' meet 'systems' as Functional or 'Aspect' Systems to enable selection of the right measures to be used in ultimate experiments.

Aspect systems are performance criterion specific aggregations over technical systems (Augenbroe, 2011). It was mentioned earlier that stakeholders' dialogues will not be constructive and suffer from discontinuity if there is no systematic specification of functional requirements, their specialization in terms of performance criteria, and their translation into individual performance requirements. Each performance requirement agreed upon must be quantifiable using a measurement method. A 'performance indictor" or PI is the representation of the actual quantification result. It should be noted that multiple PIs can be used to measure each performance requirement, however each PI is related to exactly one quantification and verification method for its quantification (Augenbroe, 2011).

Performance of motors, their controller, and DR strategy employed should be evaluated in terms of combined performance of all of them. This can only be achieved by understanding interactions among components of a system and finding meaningful methods from physics of that system to support translation of performance requirements into quantifiable performance indicators. Calculations of power, energy, and indoor air temperature are fundamental in definition of relevant and meaningful PIs. It should be noted that, power, energy, and indoor air temperature might be calculated using different set of parameters as discussed earlier. The right function can be carefully selected based on the application. For instance, if one is interested in sizing the impeller diameter, then the related equation should be used to determine the performance of power itself in regard to the attribute of interest. It should be made clear that, here, the objective is to quantify performance of power for DR applications using building control strategies. These control strategies are applied to vary those parameters used to quantify power, which are flow rate, pressure, and fan efficiency in this case. These parameters are varied by strategies such as changing damper position to control air flow. Hence, we are evaluating performance of one control strategy against another one in terms of power subjecting to standard scenarios and experiments defined in simulation environment as the controlled space substituting for a controlled lab environment.

It has been a challenging task in DR studies to even define performance requirements. Some studies have introduced meaningful factors that could be taken as performance criteria, however, they have failed in giving a standard method to measure them. For instance, Mathieu et al. (2011) presented load shape parameters such as near-base load, near-peak load, high-load duration, rise time, and fall time as illustrated in Figure 4.14 to describe load shape. These parameters can also be used to evaluate performance of a system or building in terms of demand capacity. Although rise-time, high load duration, and fall-time seem to be meaningful parameters to describe load, authors state "it is difficult to find definitions of these time intervals that yield consistent, easily interpretable results" and they work only if load shape looks similar to Figure 4.14 (Mathieu et al., 2011). Therefore, we need PIs that can be defined as functions of a set of 'quantifiable' and 'controllable' parameters and attributes, such as flow rate. Quantifiability of these parameters enable us to systematically define a range or distribution for each parameter to be used in calculation of the PI. PIs should also be defined so that they can support evaluation of power performance under different DR scenarios.

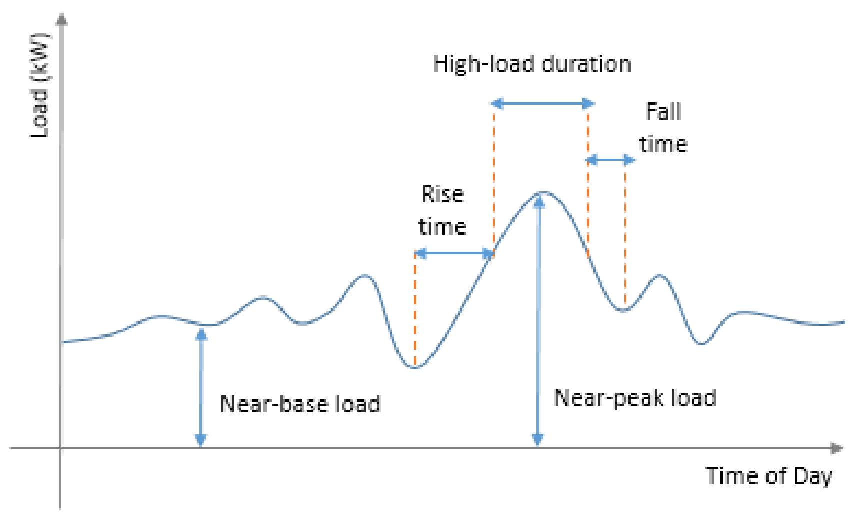



Figure 4.14 Parameters of load shape (based on Mathieu, 2011).

In the process of defining PIs for power related performance requirements, it should also be considered that assessment of power performance is different from energy performance. This is mostly because of different characteristics and behavior of power. Power changes over time in shorter time intervals and parameters affecting it vary at much faster rate compared to parameters and factors influencing energy consumption. Therefore, we cannot only rely on one quantifiable PI, such as Energy Use Intensity (EUI) measured in kWh/m$^2$/yr as used to assess energy performance. Load has multiple characteristics as illustrated in Figure 4.14 that should be taken into account when evaluating performance of power. As a result, more than one PI will be defined to assess performance of load; these PIs are functions of power and independent of how power itself is calculated.

### 4.5.1 Power Performance

Calculating power itself is a fundamental step in evaluation of power performance. Power can be modeled or determined using different methods. These can be classified as physics-based or data-driven methods. Example of data-driven method is ZIP models discussed in the previous chapter under Load Modeling in the Power System. Physics-based parameters and attributes influencing power consumption were mentioned in this chapter under Section 4.4.5. As it was mentioned earlier, the method to calculate power can be selected according to the application of interest during the design or operation phases. The PIs defined here to assess power performance, are measures based on post processing the outcomes of dynamic power and energy simulation runs. These PIs can be considered and re-used regardless of the method used to determine power consumption. Yet, it should be taken into account that in this study, the intention is to determine PIs that can be integrated with decision support systems to evaluate impact of one control strategy on power performance in a systematically defined experiment against another one. Here, the main variable of interest is fan speed, which will be discussed in detail in the following chapter. Hence, power is calculated as a function of flow rate.

Power cannot be assessed using only one indicator such as the peak $kW/m^2$ commonly used to assess energy performance of a building design against another one. This is because of some inherent characteristics and dynamic behavior of power and electricity. Therefore, more than one PI is defined here for performance criterion of power consumption. It should be mentioned that there are a number of measures such as demand factor, load factor, and diversity factor used mostly by utilities to estimate and evaluate load (Beaty and Fink, 2013). *Demand factor* is the ratio of maximum demand to the amount of total load (i.e., sum of all loads) connected. The demand factor is always less than or equal to one. The lower the demand factor, the less system capacity required to serve the connected load. *Load factor* is the ratio of average consumption (i.e., actual kWhs used in a given period of time) to by possible kWhs that could have been used during that time. The potential kWhs is calculated by multiplying the peak power use (kW) in that period of time by the number of days multiplied by the number of hours in a day. A high load factor is considered to be 'good' although it means higher energy consumption. A low load factor means inefficient use of electricity. Load factor is also used to determine demand limit (i.e., how much load can be curtailed) by considering an ideal load factor. *Diversity factor* is determined by dividing the sum of maximum demand of all loads by the maximum demand of the system. In other words, it is the ratio of installed load to the running load and it is always greater than or equal to one. Although these measures were considered in definition of PIs developed in this work, they are not directly utilized. The most applicable measure to assessment of building load for DR applications is load factor. However, the issue with this factor is that it evaluates peak inseparable from energy consumption. In other words, a high load factor is considered to be good even if it is achieved by increasing energy consumption. This is not ideal at building level so other PIs are defined to assess peak independent of energy use. Also, not using load factor avoids confusion with power factor which is the ratio of real power to apparent power.

The first PI is based on power characterization and quantification on minimum, maximum, and average power demand in a given time period (e.g., one day). Characterizing power in terms of its minimum, maximum, and average provides the basic measures for analyzing the behavior of power demand of a system, building or community of buildings at any point in time. It also supports comparing the load profile of one system, building, or DR strategy against another one. To be more specific, the first PI is defined as the ratio of maximum power demand to the average demand. Max-to-average power ratio (MAPR) is also used in power studies (more commonly referred to as peak-to-average power ratio) and hence relevant to be utilized here. This PI is used to assess load performance in terms of power 'peaking' and 'rebound.'

$$MAPR = \frac{Max(P_i)}{\frac{1}{n}\sum_{i=1}^{n} P_i} \tag{4.3}$$

The next PI should be capable of measuring power elasticity or flexibility, which is an important factor when evaluating power performance in the area of demand side management. Flexible load or demand means an energy consuming system that is capable of ramping its power demand up or down as a response to the DR signal received. Therefore, demand flexibility can be broken down into both 'demand reduction' and ‘excess absorption’ depending on the requirement. Demand flexibility can be measured by demand intensity, which is defined as power consumption per unit of time per unit of space, i.e., $\frac{\mathrm{W/min}}{ft^2}$. Power can be calculated in finer time steps using integrated thermal and power modeling presented in Chapter 3. Assuming 97.5$^{th}$ percentile of daily load is near-peak load in kW (Mathieu et al., 2011), we can calculate near-peak load per unit of space and compare that with load intensity to assess flexibility in terms of its potential for demand reduction. On the other hand, assuming 2.5$^{th}$ percentile of daily load is near-base load in kW (Mathieu et al., 2011), we can determine near-base load per $ft^2$ and evaluate demand flexibility by its potential for absorbing excess generation.

The third PI defined to measure power performance is demand disparity. Demand disparity can be determined by calculating a coefficient of variation for a period of time e.g., daily, monthly, or annually as described in Equation 3.4. The higher the demand disparity, the more power demand is deviating from the average power consumption in a given time period. Demand disparity also indicates the length of a peak or rebound[1]. Flexibility of load in terms of both demand reduction and excess absorption can also be realized from demand disparity. To minimize the length of rebound, demand disparity should be low during after DR hours i.e., after applying any advanced energy or demand saving strategy. The lower the demand disparity, the closer it is to average power use and hence not flexible. However, demand disparity does not represent the exact time

[1] A power rebound is an unwanted increase in demand immediately following any energy efficiency intervention or load reduction mechanism.

of deviation and hence not possible to use it for taking an action about the next operational decision. Figure 4.15 represents what demand disparity coefficient mean in terms of power performance and how it can be interpreted to detect flexible load or rebound.

$$\text{Demand disparity} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(P_i - \overline{P})^2}{n-1}}}{\frac{1}{n}\sum_{i=1}^{n} P_i} \qquad 4.4$$

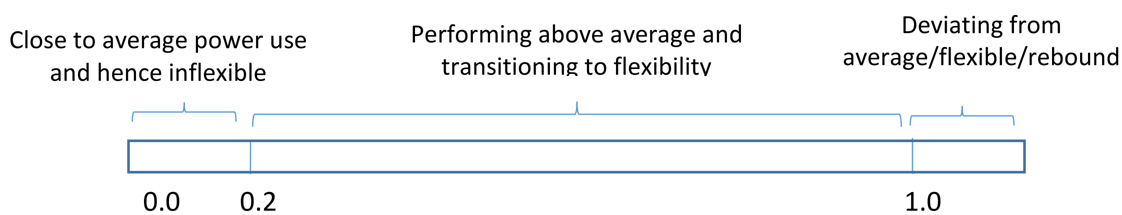



Figure 4.15 Demand disparity coefficient

The fourth measure defined to evaluate power performance is load variation in time. This PI can measure assess performance of load at certain point in time. Load factor is a measure typically used in the power grid to represent the level of peak loads over a specified period of time (Wang et al., 2014). It is defined as the average load divided by the peak load in a time period. At the building level, similar concept could be used to quantify performance of power at each time step by dividing the average power calculated for a time period (e.g., daily) under normal operation by power at each time step after implementation of a control strategy. Equation 4.5 represents quantification of this PI. Nominal power use of the system could also be used instead of the average.

$$Time_{variant} load\ (power) performance\ coef\ (PPC) = \frac{\frac{1}{n}\sum_{i=1}^{n} P_i}{P_i} \qquad 4.5$$

Let’s call this time-variant power performance coefficient (PPC). The closer this ratio is to 1, the better the system is performing in terms of power consumption to reduce peak. Basically a PPC = 1 means a balanced power consumption. If PPC<1, then power consumption is below average and if PPC>1, power use is above average. As PPC approaches zero, it indicates a larger power peak. Determination of the time interval is also important. For instance, if we find PPC within 10 minutes, the peak point (the lowest PPC found at each time step during that time interval) may or may not represent the daily peak. PPC works well for detecting or determining power dips. Figure 4.16 depicts how this concept works.

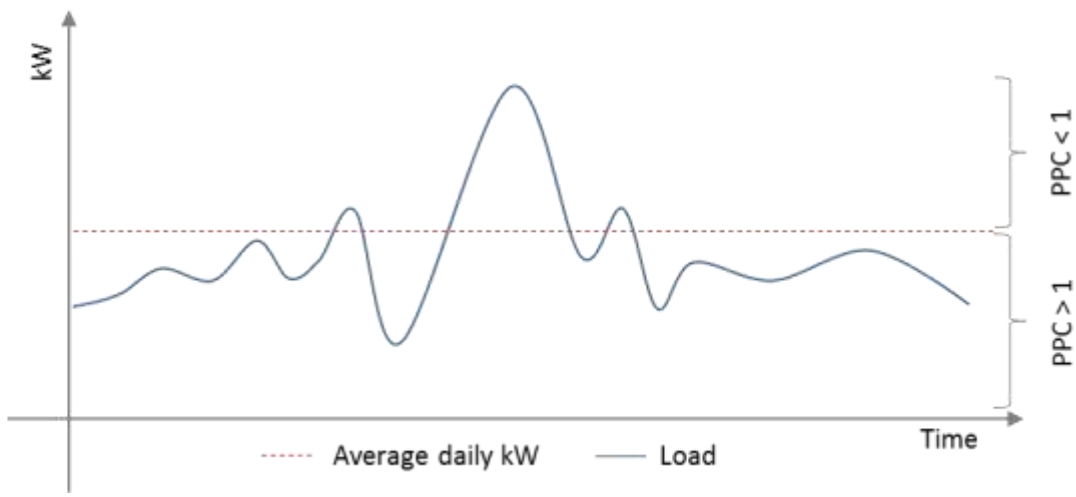



Figure 4.16 Power performance illustration

### 4.5.2 Energy Performance

Energy performance is another performance requirement that is important to maintain unless the power grid is in critical status. In fact, performance assessment and rating of buildings in terms of their power demand (i.e., power consumption during peak hours) cannot be achieved in isolation from energy performance. It is important to consider both energy efficiency and power peak reduction methods by quantifying their performance, comparing and finding the trade-off. Energy consumption of fan can be calculated using normative or detailed energy models. Here, because the focus is the air distribution system serving multi zones, EnergyPlus is used to measured fan energy use. In EnergyPlus, fan energy is calculated as a function of air flow, pressure rise, fan total efficiency and air density for a period of time e.g., hour, day, or year.

### 4.5.3 Thermal Comfort

When it comes to using buildings as assets and resources for ancillary services to support the power grid, ‘comfort’ is probably one of the most arguable topics and measures from the perspective and viewpoint of building practitioners. Hence, it should be carefully assessed.

The core function of a building is providing shelter. Buildings are supposed to provide a comfortable and healthy environment. 'Comfort’ is not an easy criterion to measure. However, concerns about thermal comfort and development of methods to measure it initiated since the 1970’s as the need for energy efficient buildings emerged. The most well-known and widely accepted thermal comfort method was first proposed by Fanger (1972) as an index called predicted mean vote (PMV). PMV is an estimate of the average thermal comfort of all occupants in a building. The PMV method is influenced by environmental and personal factors and uses a heat balance model of the human body to predict thermal sensation. PMV is a function of different parameters, which are clothing levels, indoor and outdoor air temperatures, mean radiant temperature, air movement, relative humidity, and activity levels.

Another measure used in conjunction with PMV is the percentage of dissatisfied (PPD), which predicts the percentage of occupants that will be dissatisfied with the building's thermal conditions. PPD is a function of PMV and, as shown in Figure 4.17, as PMV moves farther from 0 (neutral), dissatisfaction, as measured by PPD, increases. For example, suppose that a thermostat set point is raised by 1 degree F in response to an external grid signal. The change in set point results in a rise in building temperature, changing the PMV from 0.5 to 1.0 (PMV is measured in the range between −3.0 and 3.0), indicating that there will be an increase in the percentage of people dissatisfied (too hot in this case).

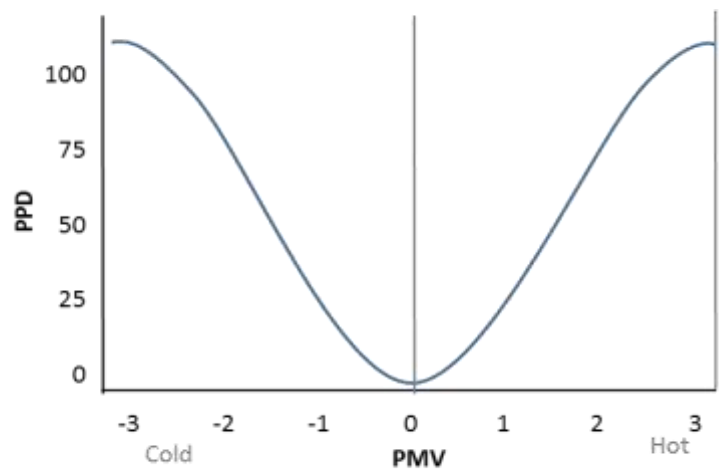



Figure 4.17 PMV-PPD Relationship

Different guidelines and steady state thermal comfort standards are developed based on these methods to rate thermal comfort levels, e.g., ASHRAE-55 (2004), EN 15251 (2007), and ISO 7730 (1994). The main objective of these standards is to specify acceptable thermal conditions for 80% or more of occupants in a given built environment. Although models based on heat-transfer and energy balance are able to account for some behavioral adaptations (e.g., clothing), they do not consider, for example, the psychological dimension of adaptation. To address this limitation, Humphreys and Nicol (1998) proposed an adaptive comfort model as an alternative to fixed temperature setpoint controls within buildings. The adaptive model considers factors beyond fundamental physics and assumes that the building is not conditioned but occupants are free to change their environment or clothing level within a range. The adaptive comfort zone would change based on the prevailing mean outdoor temperature. In this method, an adaptive comfort standard serves as an alternative to the PMV-based method. It was found that the ideal comfort temperature, $T_{comf}$, in naturally ventilated buildings is a function of the mean of monthly outdoor air temperature, $T_{out\_mean}$ (Humphreys, 1978; Auliciems & de Dear, 1986; Nicol and Raja 1995). $T_{comf}$ can be predicted by linear regression equation of the following form:

$$T_{comf} = a.T_{out\_mean} + b \qquad 4.6$$

There are different findings for $a$ and $b$. de Dear and Brager (2002), proposed $a = 0.31$ and $b = 17.8$. Humphreys (1978) and Nicol & Humphreys (2002) proposed similar values for naturally ventilated buildings outside the heating season, which are $a = 0.534$ and $b = 11.9$. McCartney and Nicol (2002) suggested that a running mean of the outdoor temperature is a better predictor of indoor comfort temperature than the monthly means used by Humphreys (1978) and hence they developed an improved adaptive comfort model based on the existing adaptive comfort model (from the European Standard).

Air temperature is the common indicator of thermal environment used in IEQ and productivity research (Lan et al., 2012) and hence used in this work to assess thermal comfort. The assumption that drives our perspective is that buildings participating in DR are equipped with HVAC system and setpoints selected by EMCS, facility managers or occupants represent a comfortable temperature range. Under this assumption, occupants are comfortable as long as the building is maintained at the thermostat setpoint temperature, $T_{setpt}$ and thermal comfort is measured as the quantity of *time* or duration (hour or minute) the space temperature deviates from the thermostat setpoint temperature (Equation 4.9). The second comfort indicator is the magnitude of temperature difference from the setpoint found by calculating the absolute of maximum temperature change in a given period of time (e.g., one day) for each strategy applied (Equation 4.10).

$$T_{comf} = T_{setpt} \tag{4.7}$$

$$\Delta T = |T_{zone} - T_{setpt}| \tag{4.8}$$

$$t_{comf} = t\left(T_{comf} = T_{setpt}\right) \quad and \quad t_{uncomf} = t\left(T_{comf} \neq T_{setpt}\right) \tag{4.9}$$

$$Magnitude\ of\ setpoint\ deviation = |\max(\Delta T)| \tag{4.10}$$

Where,

| | | |
|---|---|---|
| $T_{comf}$ | *is* | the comfort temperature |
| $T_{setpt}$ | *is* | the setpoint temperature |

| | | |
|---|---|---|
| $\Delta T$ | *is* | the deviation of zone temperature from thermostat setpoint |
| $T_{zone}$ | *is* | the zone temperature |
| $t_{comf}$ | *is* | the duration of zone temperature equal to setpoint temperature |
| $T_{uncomf}$ | *is* | the duration of zone temperature not equal to setpoint temperature |

#### 4.5.4 Responsiveness

The control process and building thermal mass result in response lags or delays that usually restrain the speed of DR (Cue et al., 2015). Therefore, response time of the controller and motor play an important role on performance assessment of building systems in the context of smart grid and power resiliency. Response time of controller and system can be calculated by simulating the controller type (e.g., PID) and system using a carefully selected modeling method as described by Henze and Neumann (2009). Measuring responsiveness is beyond the scope of this work and will be addressed in future work.

#### 4.5.5 Granularity

Although response time is a critical factor for some DR objectives such as frequency regulation, 'granularity of control' is also an important requirement. Granularity refers to "how much floor area is covered by each controlled parameter (e.g, temperature)" according to Watson et al. (2006). For instance, adjusting the setpoint is a highly granular way to distribute the DR power reduction burden throughout the facility. This is owed to the thermal mass of the building. Turning off a system is a less granular strategy which result in effective DR savings, however, occupant comfort is easily affected (Watson et al., 2006).

Granularity can be measured by 'lead time.' Lead time is defined as the latency between the initiation and execution of a process. In this context, it is defined as the time it takes for the zone to reach the adjusted setpoint and unlike response time, it is preferred to increase lead time rather than reducing it in order to maintain occupant comfort. Lead time (Equation 4.11) is a function of indoor air temperature, setpoint, outdoor air temperature, and as a result affected by building thermal mass and insulation (Huang et al., 2006).

$$t_{lead} = a\,(T_{in} - T_{set}) + b\,(T_{in} - T_{set})(T_{out} - T_{set}) + c \qquad 4.11$$

Where *a, b* and *c* are coefficients dependent on the building's thermal mass and internal loads (Huang, 2003), $T_{in}$ is the indoor initial air temperature, $T_{set}$ is the new setpoint, and $T_{out}$ is the outdoor air temperature.

### 4.5.6 Fan performance

Developing regulations for fans in the U.S. initiated only a few years ago in 2012 and not yet in place (AHRI, 2012). European fan efficiency regulations took effect on January 1, 2013, in less than two years ago (Hauer and Brooks, 2012). This shows how primitive our understanding of fan performance is. In Europe, ISO 12579 and 327/2011 EU were developed to describe performance of fans as a measure of fan motor efficiency grades (FEMG). In the U.S., the direction has been different and the metric defined is fan efficiency grade (FEG). According to ISO 12579, FMEG accounts for losses in the control system, in the electric motor, in the VSD, and also the overall aerodynamic and bearing losses (Hauer and Brooks, 2012). Efficiency quantification methods from ISO 12579, which is also followed by AMCA Standard 205 can be used to estimate fan efficiency.

### 4.5.7 Indoor Air Quality

Indoor air quality (IAQ) is another factor that should be assessed because of its impact on occupant's health and productivity. IAQ is normally assessed in terms of relative humidity, carbon dioxide levels, particles, and other contaminants in building spaces. On average, people spend up to 90% of their time indoors. Studies have evaluated the relationship between IAQ and occupant health in office buildings in three different areas (Clements-Croome 2006 and Fisk 2000). Health concerns associated with poor IAQ include sick building syndrome with symptoms such as fatigue, headache, dizziness, difficulty breathing, and irritations of the skin, eyes, and nose; asthma and allergies; and, communicable and respiratory diseases.

Fanger (1988) published an equation to estimate the number of dissatisfied occupants as a function of the perceived air pollution using the decipol unit. Equation 4.12 shows the correlation between the PPD of building occupants and the decipol level (*C*). This equation indicates that the number of dissatisfied people is a function of IAQ and airflow.

$$PPD = 395e^{(-3.25 \cdot C - 0.25)} \quad 4.12$$

Assessment of occupants' satisfaction with building IAQ is important in DR and building-grid studies because some building control strategies such as demand control ventilation (DCV) involve reduction in amount of outdoor air and air flow to reduce power consumption of AHU fans in big commercial buildings. Hence, quantifying the number of dissatisfied occupants as a result of fresh air circulation informs whether fan operation may be reduced or curtailed, and for what duration of time.

It should be noted that 'availability' is also an important criteria for DR. However, 1) this work is not about DR performance assessment and 2) we assume HVAC load, as a weather dependent load, is available. These are described in the following sections in detail.

### 4.5.8 List of Selected PIs

Table 4.1 shows a summary of a sub-set of the performance criteria, PIs and quantification methods defined in this work. These criteria as listed in Table 4.1 include power performance, energy performance, and thermal comfort.

Table 4.1 Performance Criteria, Indicators, and Quantitative Methods

| *Performance criteria* | *PI #* | *PI Name* | *Quantitative Method* |
|---|---|---|---|
| **Electric energy (power) performance** | 1 | Peak or rebound formation | Peaks or rebound formation are quantified by calculating the ratio of maximum demand to average power demand. |
| | 2 | Demand intensity | Power consumed in a given time interval normalized by the area of thermal zone served. |
| | 3 | Demand disparity | Demand disparity coefficient (Equation 3.4) |
| | 4 | Power performance coefficient | Time-variant load coefficient |
| **Energy performance** | 5 | Energy consumption | E+ or normative methods |
| **Thermal comfort** | 6 | Temperature deviation from setpoint and its duration | Deviation of space temperature from setpoint and its duration |

## 4.6 The Overall Performance Framework Defined

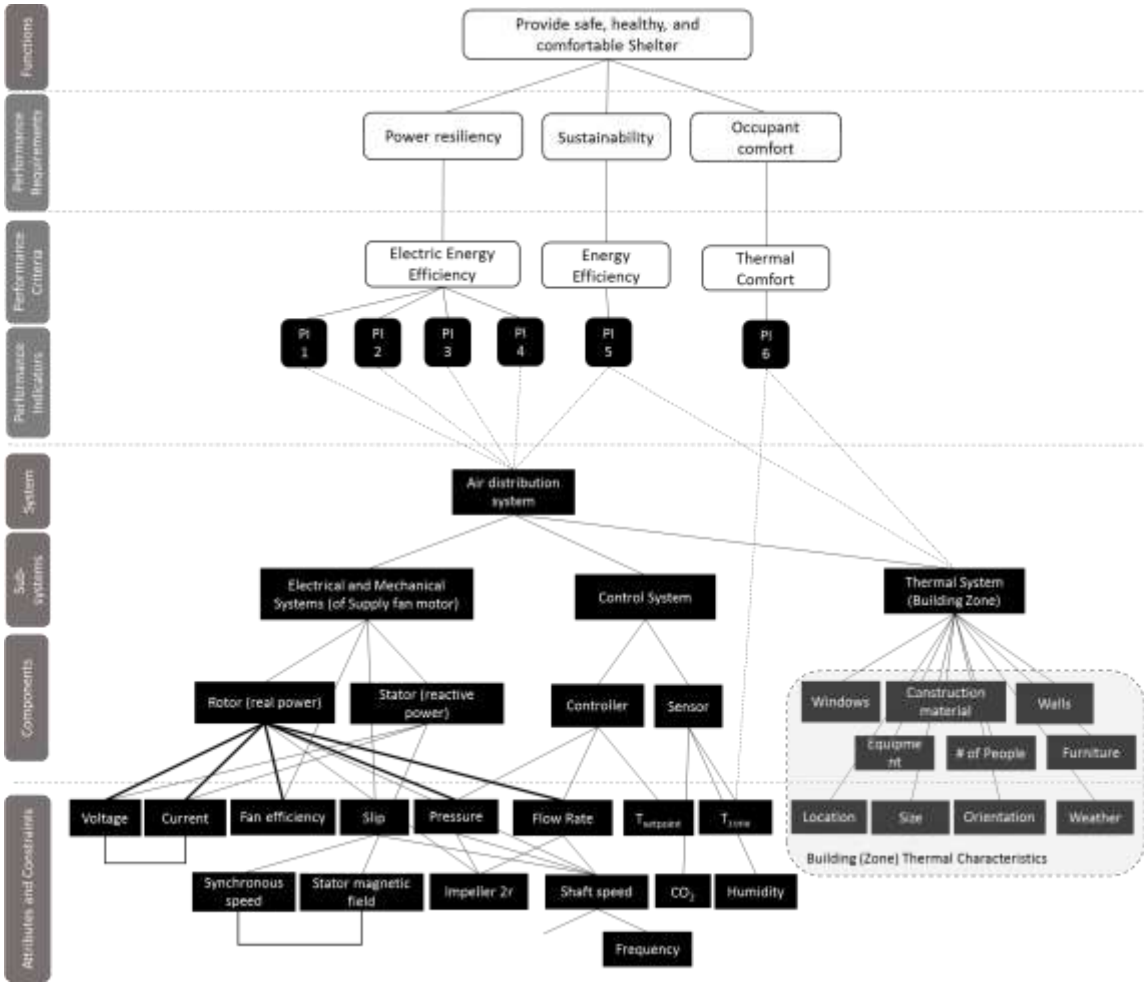


Figure 4.18 Performance framework with a focus on electric energy performance.

## 4.7 Discussion and Conclusions

This chapter defines a power performance framework for an AHU supply fan. It illustrates how power consumption is influenced by one building system (i.e., fan) from the lowest non-physical component level of that system to the highest functional level of the building itself. This approach supports performance assessment from multiple perspectives, which are expressed as performance criteria. The top-down functional decomposition and bottom-up technical system aggregation approach is adopted to structure a performance tree that supports identification of these performance criteria and their associated quantifiable measures. Quantification methods are then carefully selected and introduced for each quantifiable PI to measure the effectiveness of an HVAC control alternative in the context of DR to fulfill performance requirements and criteria defined for each function identified. It should be mentioned that, the number of PIs mentioned and discussed are more comprehensive than those actually selected for further analysis in this work. Hence, quantification methods are only derived for the PIs applicable to the context and modeling methods of this dissertation. Other PIs introduced are beyond the scope of this work and will be dealt with in future work.

Discussing functions, understanding physics of the problem, system types, interactions among systems and elements, their characteristics, controller scheme, and other aspects mentioned in this chapter intend to support identifying parameters that affect fan motor performance. This is significant for formulation of effective performance quantification methods to rate power performance of building systems. Having a systematic approach to quantify performance of power in a building leads us to better coupling and integration of energy efficiency measures with power performance measures (e.g., DR).

Quantifiable power PIs are integral components of a facility decision support system for energy and power management in addition to planning and management of power in the power system. Without such indicators, one cannot capture the impact of one HVAC control strategy against another. For instance, if a building has a high energy consumption or power demand and the facility manager decides to select a mechanism to lower consumption, he cannot make a rational decision without the right evaluation metrics that are quantifiable and hence comparable. Therefore, metrics defined are essential in automated building EMCS and the facility manager i.e., decision maker for calculating the trade-off between two alternative options. These metrics are also important for power management in the electricity system for estimating the impact of different energy and demand reduction methods including building energy efficiency methods (EEMs) and retrofits on load forecasting in short or long-term periods.

The next chapter covers power performance assessment of a system (AHU supply fan) under different conditions using PIs established in this chapter. Different control strategies for energy and power reduction are introduced and their performance are evaluated when applied to an AHU fan to rank the HVAC control strategies, which are the DR control strategies at building level. The platform used to model different control strategies for this demand performance assessment is EnergyPlus simulation environment. This detailed building energy modeling tool is selected for performance evaluation because of its capability to support multi-zone buildings and a variety of HVAC control strategies at AHU supply fan level. Furthermore, application of these metrics for energy and power performance prediction in load forecasting models (data-driven approach) will be illustrated.

# 5. POWER PERFORMANCE ASSESSMENT OF BUILDING CONTROL STRATEGIES FOR DEMAND SIDE MANAGEMENT

## 5.1 Introduction

A set of performance indicators (PIs) were defined using the performance framework developed in the previous chapter. Each PI is calculated by subjecting the chosen (fixed) system to a set of normative scenarios. These scenarios are defined and modeled in a controlled simulation environment to understand how well they capture and quantify the performance criterion they are supposed to measure. The numerical outcome obtained are used to rank different control solutions.

The objective of this work is to systematically evaluate the performance of different HVAC control strategies e.g., temperature adjustment and demand control ventilation, that can be implemented for energy and power management using a set of performance indicators identified in the previous chapter. Prior to performance evaluation of control strategies under different DR scenarios, a review of building types, HVAC systems that can be deployed, and control strategies available are presented. It is important to understand the building types, systems, and control systems (EMCS) to be able to make an informed decision about execution of a control strategy for DSM/DR depending on the application and scenario of use. The objectives of this decision are minimizing energy consumption and maximizing electric demand savings while minimizing negative impacts on IAQ and the building occupants.

## 5.2 Background

### 5.2.1 Commercial Building Use Types

The function (i.e., use type) of a building is strongly tied to its design and construction. In the Commercial Buildings Energy Consumption Survey (CBECS), buildings are classified according to their principal activity, which is the primary business, commerce, or other function carried on within each building (EIA, 2012). Building types and their definitions according to CBECS are included in

Table 5.1. Beside design and construction, the function or use type of buildings affect operational decisions of facility managers although their decisions for managing a facility are based on preferences and activity type of occupants in each space. Therefore, knowing the building type and its function is an important criterion for DR decisions.

Table 5.1 Building Type Definitions based on CBECS (EIA, 2012)

| ***Building type*** | ***Definition*** |
|---|---|
| **Education** | Buildings used for academic or technical classroom instruction, such as elementary, middle, or high schools, and classroom buildings on college or university campuses. Buildings on education campuses for which the main use is not classroom are included in the category relating to their use. For example, administration buildings are part of "Office," dormitories are "Lodging," and libraries are "Public Assembly." |
| **Food sales** | Buildings used for retail or wholesale of food. |
| **Food service** | Buildings used for preparation and sale of food and beverages for consumption. |
| **Health care (inpatient)** | Buildings used as diagnostic and treatment facilities for inpatient care. |

Table 5.1 Continued

| ***Building type*** | ***Definition*** |
| --- | --- |
| **Education** | Buildings used for academic or technical classroom instruction, such as elementary, middle, or high schools, and classroom buildings on college or university campuses. Buildings on education campuses for which the main use is not classroom are included in the category relating to their use. For example, administration buildings are part of "Office," dormitories are "Lodging," and libraries are "Public Assembly." |
| **Food sales** | Buildings used for retail or wholesale of food. |
| **Food service** | Buildings used for preparation and sale of food and beverages for consumption. |
| **Health care (inpatient)** | Buildings used as diagnostic and treatment facilities for inpatient care. |
| **Health care (outpatient)** | Buildings used as diagnostic and treatment facilities for outpatient care. Medical offices are included here if they use any type of diagnostic medical equipment (if they do not, they are categorized as an office building). |
| **Lodging** | Buildings used to offer multiple accommodations for short-term or long-term residents, including skilled nursing and other residential care buildings. |
| **Mercantile (retail other than mall)** | Buildings used for the sale and display of goods other than food. |
| **Mercantile (Enclosed and Strip Malls)** | Shopping malls comprised of multiple connected establishments. |
| **Office** | Buildings used for general office space, professional office, or administrative offices. Medical offices are included here if they do not use any type of diagnostic medical equipment (if they do, they are categorized as an outpatient health care building). |
| **Public assembly** | Buildings in which people gather for social or recreational activities, whether in private or non-private meeting halls. |

Table 5.1 Continued

| *Building type* | *Definition* |
|---|---|
| **Public Order and Safety** | Buildings used for the preservation of law and order or public safety. |
| **Religious worship** | Buildings in which people gather for religious activities, (such as chapels, churches, mosques, synagogues, and temples). |
| **Service** | Buildings in which some type of service is provided, other than food service or retail sales of goods |
| **Warehouse and Storage** | Buildings used to store goods, manufactured products, merchandise, raw materials, or personal belongings (such as self-storage). |
| **Other** | Buildings that are industrial or agricultural with some retail space; buildings having several different commercial activities that, together, comprise 50 percent or more of the floorspace, but whose largest single activity is agricultural, industrial/ manufacturing, or residential; and all other miscellaneous buildings that do not fit into any other category. |
| **Vacant** | Buildings in which more floorspace was vacant than was used for any single commercial activity at the time of interview. Therefore, a vacant building may have some occupied floorspace. |

### 5.2.2 HVAC Systems

Following ASHRAE HVAC system types from ASHRAE 90.1.2010, there are 6 system types specified for commercial buildings (excluding heated only storages). These are system numbers 3 through 8 as specified in Table G3.1.1B of ASHRAE 90.1.2010 and listed here in Table 5.2. It is important to know HVAC system types, because the applicable control strategy for DSM/DR can be determined based on these system types.

Table 5.2 HVAC System Type Classification based on ASHRAE 90.1.2010

| *System No.* | *System Type* | *Fan Control* | *Cooling Type* | *Heating Type* |
|---|---|---|---|---|
| **ASHRAE3** | Packaged | CAV | DX | Furnace |
| **ASHRAE4** | Packaged | CAV | DX | Heat pump |
| **ASHRAE5** | Packaged | VAV | DX | Boiler |
| **ASHRAE6** | Packaged | VAV | DX | Electric resistance |
| **ASHRAE7** | Central | VAV | Chilled water | Boiler |
| **ASHRAE8** | Central | VAV | Chilled water | Electric resistance |

The DOE's Commercial Prototype Building Models were constructed to represent 80% of the commercial building floor area in the United States for new construction, including both commercial buildings and mid- to high-rise residential buildings (DOE, 2014). System types used in these models are summarized in Table 5.3 below. This sample indicates the most common types of systems used in different building types to help with the determination of the most suitable control strategy for different building and system types.

Table 5.3 System Types and Air Distribution System Based on Building Type

| **Building Type** | **Cooling Type** | **Heating Type** | **Air Distribution** |
|---|---|---|---|
| **Small Office** | Air-source heat pump | Air-source heat pump with gas furnace as back up | Single zone, CAV, one unit per occupied thermal zone |
| **Medium Office** | Packaged air conditioning unit | Gas furnace inside the packaged air conditioning unit | VAV terminal box with damper and electric reheating coil |

Table 5.3 Continued

| **Building Type** | **Cooling Type** | **Heating Type** | **Air Distribution** |
|---|---|---|---|
| **Large Office** | 1. Water-source DX cooling coil for datacenter and IT closets<br>2. Two water-cooled centrifugal chillers for the rest of the building | Gas Boiler | VAV terminal box with damper and hot-water reheating coil |
| **Stand-alone Retail** | Packaged air conditioning unit. | Gas furnace inside the packaged air conditioning unit | CAV |
| **Strip Mall** | Packaged air conditioning unit | Gas furnace inside the packaged air conditioning unit | 10 single-zone rooftop units with CAV. One unit serving one store. |
| **Primary School** | Packaged air conditioning unit | 1. Gas furnace inside packaged air conditioning unit<br>2. Hot water from a gas boiler for heating | 1. CAV systems: direct air from the packaged air conditioning unit<br>2. VAV systems: VAV terminal box with damper and hot water reheating coil |
| **Secondary School** | 1. Packaged air conditioner<br>2. Air-cooled Chiller | 1. Gas furnaces inside packaged air conditioning units<br>2. Gas-fired boiler | 1. CAV system: direct air from the packaged unit<br>2. VAV System: VAV terminal box with damper and hot water reheating coil |
| **Outpatient Healthcare** | DX cooling coil | Gas boiler | VAV terminal box with damper and hot water reheating coil<br>Electric resistance reheat in AHU-2 |
| **Hospital** | Two water cooled centrifugal chiller | Gas boiler | 1. Medical critical zones: five VAV with hot water reheating and electric stream humidifiers.<br>2. Non-critical zones: two VAV systems for general zones<br>3. One CAV for kitchen zone. |

Table 5.3 Continued

| Building Type | Cooling Type | Heating Type | Air Distribution |
|---|---|---|---|
| **Small Hotel** | 1. Guest rooms and corridors: PTAC<br>2. Public space: Split system with DX cooling | 1. Guest rooms: PTAC with electric resistance heating<br>2. Public spaces (office, laundry, lobby, and meeting room): gas furnace inside the packaged air conditioning units<br>Storage and stairs: electric cabinet heaters | CAV |
| **Large Hotel** | One air-cooled chiller | One gas-fired boiler | 1. Public spaces on ground floor and top floor: VAV with hot water reheating coils<br>2. Guest Rooms: dedicated outside air system + four-pipe fan-coil units. |
| **Quick Service Restaurant** | Packaged air conditioning unit | Gas furnace inside the packaged air conditioning unit | Single zone, CAV |
| **Full Service Restaurant** | Packaged air conditioning unit | Gas furnace inside the packaged air conditioning unit | Single zone, CAV |
| **Apartment Midrise** | Split system DX (1 per apt) | Gas Furnace | CAV |
| **Apartment Highrise** | Water Source Heat Pumps | Water Source Heat Pumps | CAV |

### 5.2.3 HVAC Control Strategies

There are different controllable loads in commercial buildings that can be used in DR. The major electricity users in buildings are the HVAC systems, lighting, plug loads, and elevators. There have been several studies and work that have looked into the use of HVAC in DR e.g., Motegi et al., 2007; Wang et al., 2014; and Watson et al., 2006. The focus of this study is also on HVAC and more particularly on its control strategies. In this section, a broader control strategies applicable at different system and components levels are discussed. However, in the following sections, certain control strategies are selected for further evaluation and discussion.

Building energy management systems include a combination passive and active control of energy distribution. Passive control means constant volume or flow and active control means variable volume or flow which is controlled by the system based on a set of if-then conditional rule sets. To achieve this, the monitoring system gathers data (analog inputs e.g., temperature, flow, pressure) and status (discrete inputs e.g., on/off equipment status), evaluates the changes in conditions (e.g., internal load, OA temperature) based on the set of pre-defined rules and the control system *acts* accordingly. The output of the control system may also be analog or discrete. An analog output is a physical action of a proportional device in the controlled equipment e.g., actuator opens air damper from 10% to 30%. A discrete output is a response to a *status* such as starting or stopping the pumps, fans, two-position dampers, or performing on/off control. Hence, there are different controllable inputs (i.e., parameters) in and HVAC system and a number of control points with sensors to collect and report data and status. The common control inputs are: temperature, pressure, humidity, flow, and $CO_2$. Voltage and current may also be monitored at certain locations. Sensors used to collect data and status of these inputs are installed at certain control points. Figure 5.1 shows a schematic of an AHU and chiller and some control points such as supply air temperature, supply fan status, return air $CO_2$, return air temperature, and so on.

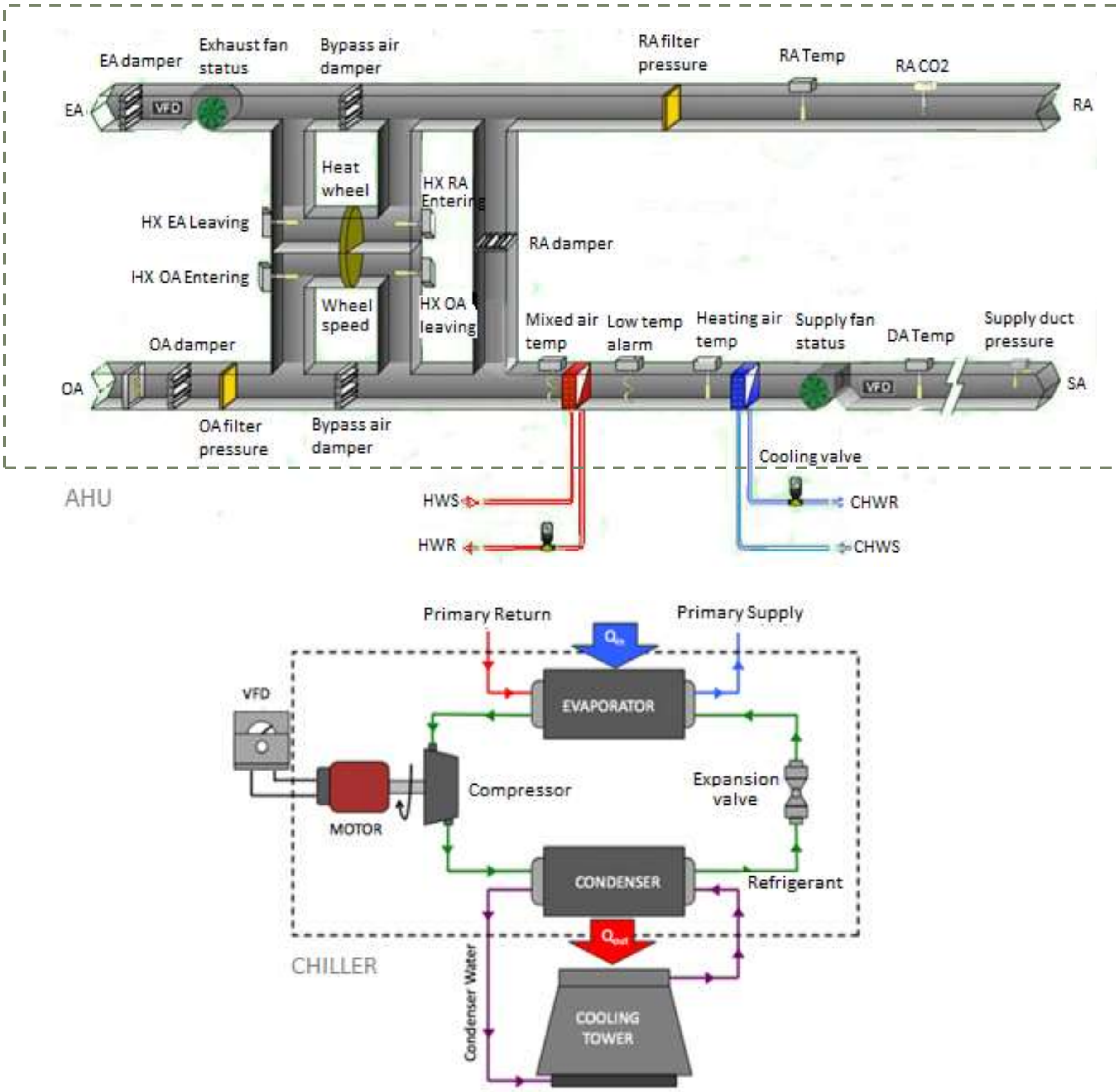
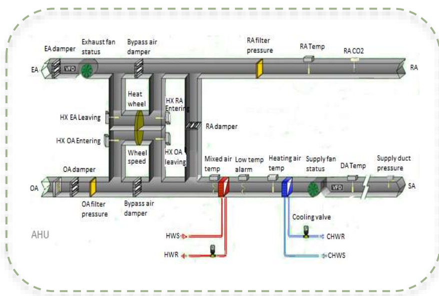
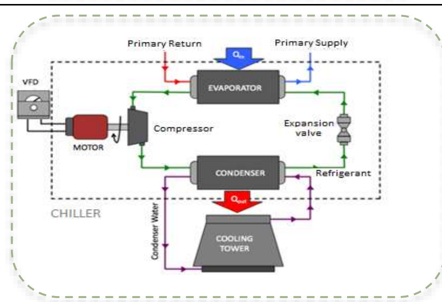



Figure 5.1 Schematic of an AHU and chiller showing different control points in the HVAC.

The basic process in the AHU as shown in Figure 5.1 is that OA enters the AHU and passes through the heat wheel. After leaving the heat wheel, air passes through a heating coil, a cooling coil and usually through a steam humidifier before it is supplied to the space being conditioned. Depending on the internal load in the space, the air gains or loses heat and moisture and then returns to the AHU. After passing the heat wheel, it finally gets exhausted to outdoors. The process in the chiller is as marked by arrows in Figure 5.1.

Knowing the details of the system and its processes helps identifying control strategies. There are common HVAC control algorithms used for normal operation of the system and there are a number of them which are specifically deployed in commercial building HVAC systems for DSM/DR to reduce or shift load. These can be summarized as: global temperature setpoint adjustment, supply air temperature increase, supply fan speed reduction, duct static pressure reduction, rooftop unit shutdown, chilled water temperature increase, chiller demand reduction, boiler lockout, pre-cooling of building thermal mass, and light dimming (Motegi, et al., 2007 and Kim et al., 2013). These control strategies are classified and listed in Table 5.4 along with their definitions and system types (*see system numbers in Table 5.2*) they can be applied to.

Table 5.4 Summary of control strategies used in DR classified by location of control point.

| Control Space | Control Point | Control Strategy |
|---|---|---|
| Thermal zone (Demand) |  | Setpoint adjustment<br>Pre-cooling |
| AHU (Distribution) |  | Reducing duct static pressure<br>Limiting fan VFD (change speed or flow rate)<br>Demand control ventilation (DCV)<br>Increasing supply air temperature<br>Reducing fan quantity<br>Limiting cooling valve |
| Plant (Supply) |  | Increasing chilled water temperature<br>Limiting chiller demand<br>Reducing chiller quantity (staging) |

## 5.3 Case Study and Implementation

A case study is set up to create a context for the performance evaluation metrics described in the previous chapter. This intends to verify the use and applicability of PIs developed. In addition to that, through this case study, a more detailed power performance assessment of HVAC control strategies for peak management in DSM and DR applications is provided. This case study can be considered as a set of experiments designed and simulated. To achieve this, different control strategies are modeled in a single story building located in Richland, WA using EnergyPlus™ modeling and simulation engine. The building, system type, and weather conditions have been kept constant in this study (i.e., one building type, one system type, and one day) in order to evaluate performance of different control strategies under different scenarios but in a controlled environment. By keeping the building, system, and weather conditions the same, we can ensure consistent and robust assessment and comparison across the performance of different control strategies implemented. This shall yield to identification and selection of the most effective mechanism for a given scenario. Furthermore, comparison of different control strategies for the same building under different scenarios indicate applicability and potential use of PIs developed of automated building energy management systems.

### 5.3.1 Building Description

The building used in this case study (Figure 5.2) is a 2,120 square meter single story building constructed in 2015 providing both office and laboratory spaces. This building is located in Richland, WA. In addition to office spaces, there are three control rooms (including the campus control center), laboratories focused on power electronics and interoperability, outdoor testing pads, EV charging stations, data storage and computing capability. The center used to monitor energy use and system performance of buildings across campus is also located in this building.

Figure 5.2 View of the main entrance of building used in the case study

This building was modeled in EnergyPlus™ using design, construction, and material specifications as summarized in Table 5.5. Other parameters and specifications used to model the building, such as thermal zoning and HVAC system are discussed in the following sub-sections. The lighting intensity in the building was modeled to be 3.28 W/m$^2$, the number of people (m$^2$/person) varies between 4.6 to 18.5 m$^2$/person from zone to zone with an average of 14.8 m$^2$/person. Plug and process has a minimum of 1 W/m$^2$ and maximum of 53 W/m$^2$ with an average of 13.6 W/m$^2$.

Table 5.5 Design specifications of the building used in the case study as used in the EnergyPlus™ model.

| | |
|---|---|
| **Exterior walls** | |
| Construction | Steel-Frame Walls |
| U-factor [W/m2-K] | 0.323 |
| Dimensions | based on floor area and aspect ratio |
| Tilts and orientations | vertical |
| **Roof** | |
| Construction | Built-up Roof:<br>Roof membrane + Roof insulation + metal decking |
| U-factor [W/m2-K] | 0.153 |
| Tilts and orientations | horizontal |

Table 5.5 Continued

| **Window** | |
|---|---|
| Dimensions (WWR) | 11% window to wall ratio (WWR) |
| Glass-Type and frame | Double Pane, Tinted<br>Nonresidential; Vertical Glazing |
| U-factor (W / m$^2$ * °K) | 3.045 |
| SHGC (all) | 0.428 |
| Operable area | 0 |
| **Foundation** | |
| Foundation Type | Slab-on-grade floors (unheated) |
| Construction | 8" concrete slab poured directly on to the earth |
| Floor U-factor (W / m$^2$ * °K) | 3.212 |
| Dimensions | based on floor area and aspect ratio |
| **Interior Partitions** | |
| Dimensions | based on floor plan and floor-to-floor height |
| Infiltration | 0.00056896, !- Flow per Exterior Surface Area {m3/s-m2}<br>Fraction of 0.25 during occupied hours (6am to 6pm)<br>Fraction of 1.0 during unoccupied hours |

*Thermal zoning*

This LEED Gold-certified facility is served by five air handling units (AHUs) using district heating and cooling. The layout of the building and thermal zones are as shown and marked in Figure 5.3. Results analyzed and discussed in this study are based on AHU1, which serves the largest zone (area) in this building. Figure 5.4 illustrates the building model in EnergyPlus™.


Figure 5.3 Building thermal zones.

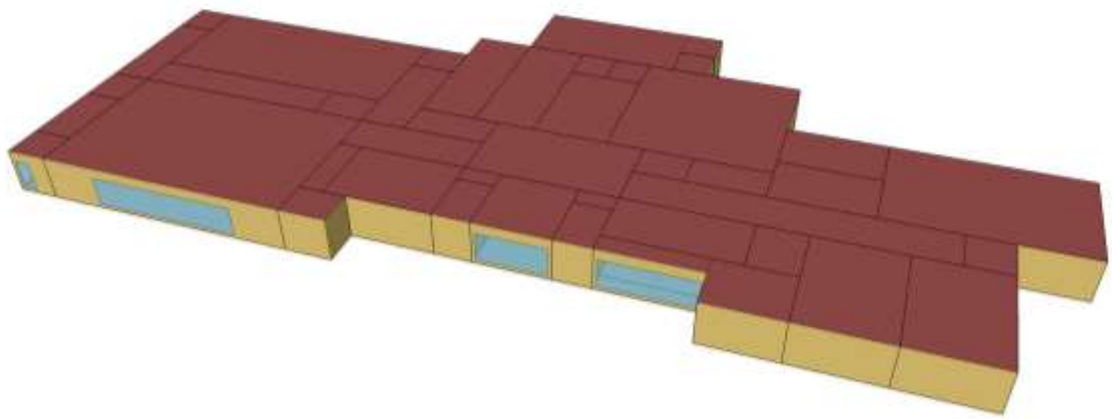


Figure 5.4. EnergyPlus™ model of the building.

*HVAC*

The AHU utilizes a central chiller to provide the chilled water needed for cooling within the building. The VAV air flow set point is reset to maintain the zone temperature at set point. The zone temperature setpoint is within 21 °C ± 1 °C range during occupied hours and 18°C to 27 °C during unoccupied hours. When zones are not occupied, the zone temperature setpoint is 23 °C ± 3C °C as the standby mode. The terminal box collects all the occupancy information from each zone to adjust the system operating specifications.

The air flow has high and low airflow setpoints. The minimum cooling and heating airflow setpoints are determined by the ASHRAE standard 62.1. The zone damper is modulated to maintain the measure airflow at the set point. The controllable points are minimum airflow setpoint, maximum airflow setpoint, zone temperature setpoint, heating offset, cooling offset, standby offset, un-occupied heating setpoint, unoccupied cooling setpoint, heating valve output, and damper output.

Table 5.6 HVAC system specifications as modeled in EnergyPlus.

| | |
|---|---|
| **System Type** | |
| Heating type | Hot water coil inside the packaged air conditioning unit served by a natural gas boiler |
| Cooling type | Rooftop AHU's receiving district chilled water |
| Distribution and terminal units | VAV terminal box with damper and electric reheating coil<br>Zone control type: minimum damper position is calculated using the multiple-zone calculation procedure |
| **HVAC Sizing** | |
| Air Conditioning | Sized based on as built specifications |
| Heating | Sized based on as built specifications |
| **HVAC Efficiency** | |
| Air Conditioning | N/A - cooling coils receiving district chilled water |
| Heating | 87% Efficient Natural Gas Boiler |
| **HVAC Control** | |
| Thermostat Setpoint | 21.1 °C Cooling/20°C Heating |
| Thermostat Setback | 26 °C Cooling/15.6°C Heating |
| Supply air temperature | 12.5, !- Central Cooling Design Supply Air Temperature {C} |
| Economizers | Control type: differential dry bulb |
| Ventilation | ASHRAE Ventilation Standard 62.1 |
| Energy Recovery | ASHRAE 90.1 Requirements |
| **Supply Fan (AHU1)** | |
| Supply Fan Total Efficiency (%) | 70% |
| Supply Fan Pressure Drop | 498 (Pa) |

*Schedules*

Schedules in the base models are determined mostly based on regular office building schedules as specified in DOE prototype commercial buildings. These schedules for fan, occupancy, lighting, plug load, and temperature setpoints during weekday and weekends are as shown in Figure 5.5, Figure 5.6, Figure 5.7, and Figure 5.8.

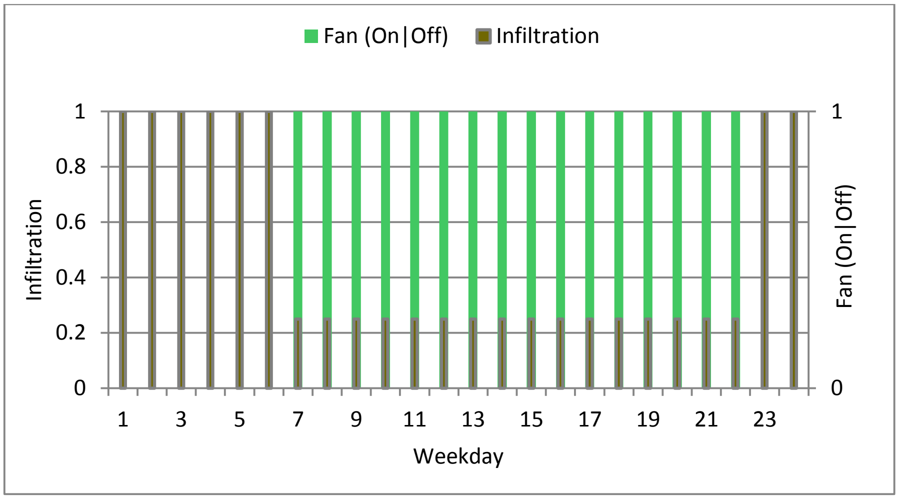



Figure 5.5 Fan schedule and infiltration rate.

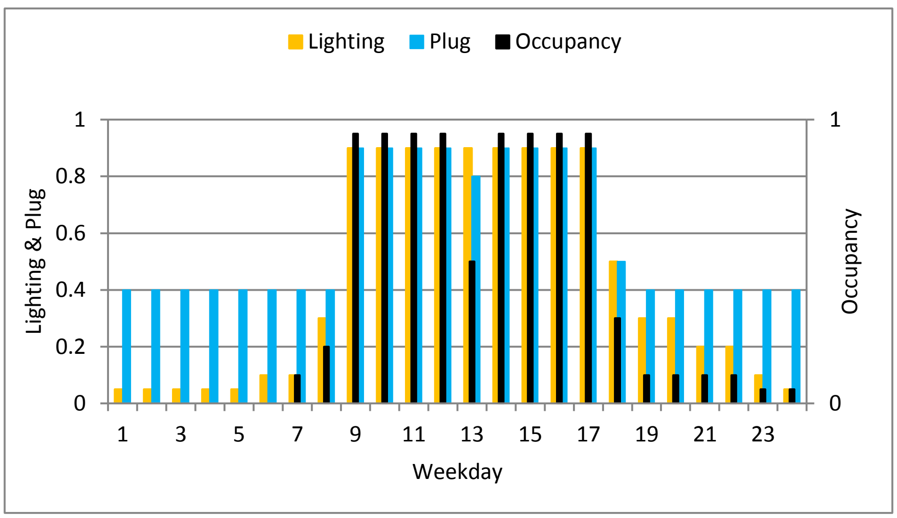



Figure 5.6 Lighting, plug load, and occupancy schedules.

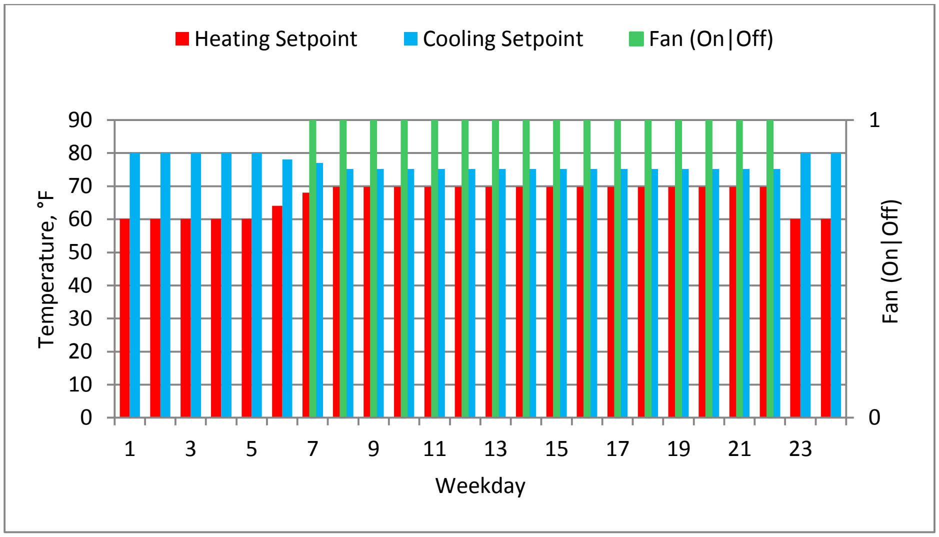



Figure 5.7 Heating, cooling, and fan schedules.

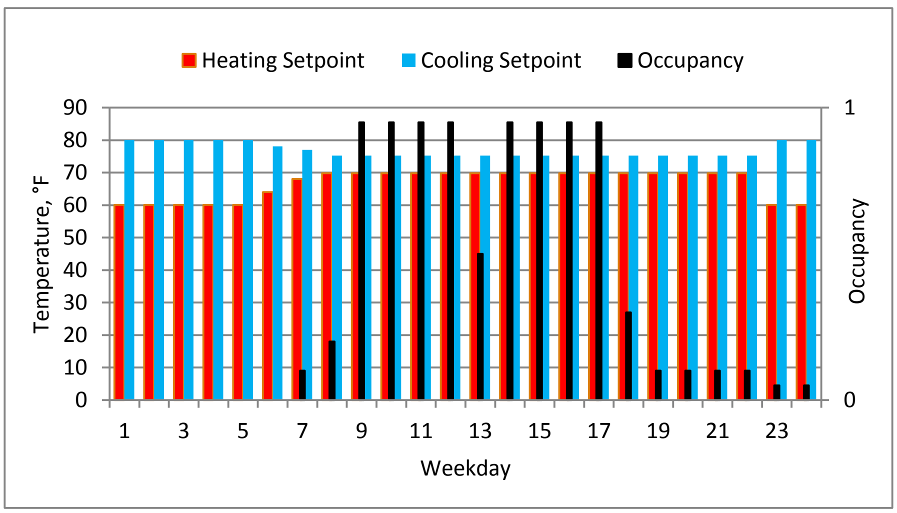



Figure 5.8 Heating, cooling, and occupancy schedules

*Weather*

The typical meteorological year (TMY3) data sets is used to simulate the buildings. Figure 5.9 shows other weather parameters as specified in the EnergyPlus™ model.

```
Site:Location,
    Pasco WA USA Design Conditions,  !- Name
    46.27,                   !- Latitude {deg}
    -119.12,                 !- Longitude {deg}
    -8.0,                    !- Time Zone {hr}
    136.00;                  !- Elevation {m}

! Pasco Annual Cooling Design Conditions Wind Speed=3.1m/s
Wind Dir=330
! Hottest Month=JUL
! Pasco WA USA Annual Cooling (DB=>MWB) .4%, MaxDB=37.5°C
MWB=21.1°C
SizingPeriod:DesignDay,
    Pasco Ann Clg .4% Condns DB=>MWB,  !- Name
    7,                !- Month
    21,               !- Day of Month
    SummerDesignDay,  !- Day Type
    37.5,             !- Maximum Dry-Bulb Temperature {C}
    17.8,             !- Daily Dry-Bulb Temperature Range
{deltaC}
    DefaultMultipliers,      !- Dry-Bulb Temperature Range
Modifier Type
          Wetbulb,       !- Humidity Condition Type
    21.1,          !- Wetbulb or DewPoint at Maximum Dry-Bulb
{C}
    99702.,        !- Barometric Pressure {Pa}
    3.1,           !- Wind Speed {m/s}
    330,           !- Wind Direction {deg}
    No,            !- Rain Indicator
    No,            !- Snow Indicator
    No,            !- Daylight Saving Time Indicator
    ASHRAETau,     !- Solar Model Indicator
    0.398,         !- ASHRAE Clear Sky Optical Depth for Beam
Irradiance (taub) {dimensionless}
    2.219;         !- ASHRAE Clear Sky Optical Depth for
Diffuse Irradiance (taud) {dimensionless}
```

Figure 5.9 Weather Station Location and Parameters as Specified in the EnergyPlus Model

### 5.3.2 Control Strategies and Scenarios Implemented

A set of HVAC control strategies were selected to be implemented in the building described. There are three classifications based on the location of the control points (as mentioned in Table 5.4). These locations are: 1) thermal zone, 2) air distribution, and 3) main plant. The building used in this case study uses district heating and cooling; therefore, there is no control option that can be specified at building level for the central plant. As a result, the control strategies described and implemented in this building are either specified at zone level (e.g., increasing or decreasing the zone temperature) or at AHU level (e.g., air flow setpoint change).

The control strategies considered and implemented in this case study are: 1) setpoint increase, 2) setpoint reduction, i.e., pre-cooling, 3) fan shut-down, 4) reducing fan flow rate, 5) demand control ventilation (DCV), and 6) combined strategy. These strategies are listed and briefly described in Table 5.7.

Table 5.7 List of control strategies defined to generate DR scenarios

| **Control Strategy** | **Description** |
|---|---|
| AHU fan powered off | AHU fan is powered off during DR period. |
| AHU fan speed reduced (airflow reduced to 1 kg/s) | AHU fan is limited to 1 kg/s during DR period, typical operation is 4 kg/s, fan max flow is 9.5 kg/s |
| AHU fan speed reduced (airflow reduced to 3 kg/s) | AHU fan is limited to 3 kg/s during DR period, typical operation is 4 kg/s, fan max flow is 9.5 kg/s |
| Pre-cooling (AirTempSetpt increased by 2°C) | Zone Air Temperature Cooling Setpoint is increased by 2°C during DR period. Volume of conditioned OA supplied to the space is not changed |
| Pre-cooling (AirTempSetpt increased by 3°C) | Zone Air Temperature Cooling Setpoint is increased by 3°C during DR period. Volume of conditioned OA supplied to the space is not changed |
| Pre-cooling (AirTempSetpt increased by 4°C) | Zone Air Temperature Cooling Setpoint is increased by 4°C during DR period. Volume of conditioned OA supplied to the space is not changed |

Table 5.7 Continued

| | |
|---|---|
| AirTempSetpt reduced 2°C | Zone Air Temperature Cooling Setpoint is reduced by 2°C during DR period.<br>Volume of conditioned OA supplied to the space is not changed |
| AirTempSetpt reduced 3°C | Zone Air Temperature Cooling Setpoint is reduced by 3°C during DR period.<br>Volume of conditioned outside air supplied to the space is not changed |
| AirTempSetpt reduced 4°C | Zone Air Temperature Cooling Setpoint is reduced by 4°C during DR period.<br>Volume of conditioned OA supplied to the space is not changed |
| DCV - Reduce Amount of Outdoor Air | Volume of OA is first increased before DR period and then reduced during DR period such that total volume of OA remains unchanged |
| Reduce Amount of Outdoor Air and Control Fan Simultaneously | Volume of OA is first increased (damper from 0.33 to the levels specified in the sched) and then reduced to zero such that total volume of OA remains unchanged.<br>In addition, AHU fan is powered off when outside air is volume is reduced. |

Each control strategy has a definition (e.g., changing setpoint) and a degree of variation (e.g., -4°C to +4°C) that can be assigned to it as depicted on the left side of Figure 5.10. These control specifications combined with DR specifications (hour and duration) result in a scenario. More than 100 scenarios were defined in the case study discussed in this Chapter and most of them were modeled in EnergyPlus™. However, a subset of these scenarios were selected for the purpose of performance assessment study included here. The number of scenarios were reduced in the analysis to better present the results. The quality of the assessment is not compromised by this reduction because only the scenarios that performed similarly or the same were eliminated from the analysis.

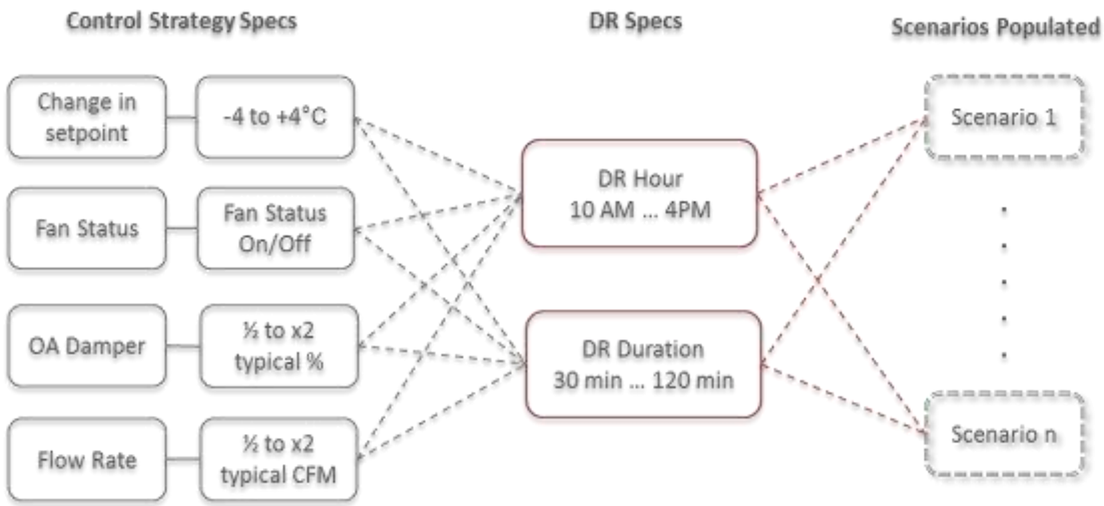



Figure 5.10 The process of generating scenarios implemented in the case study.

Each control strategy specified in Table 5.7 was modeled in EnergyPlus™ for the building described. DR specifications were modeled by modifying the schedules for each scenario defined. Scenarios implemented were simulated at 5-minute timestamps for a few days in July. Results were extracted from EnergyPlus™ output files for one day (July 6$^{th}$) for post processing to analyze data using performance metrics described in Section 4.5.

## 5.4 Time Series Results

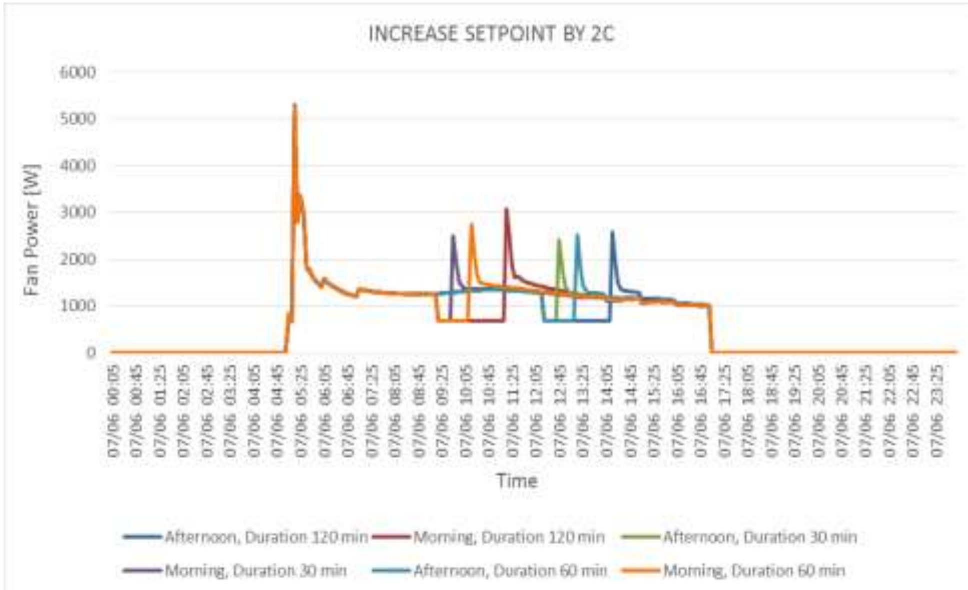
After running all scenarios, time series simulation data are extracted for further performance study and assessment. Results can be sorted and presented in different ways. Figure 5.11 Increasing setpoint by a) 2°C, b) 3°C, and c) 4°C. to Figure 5.15 illustrate load shape classification per control strategy applied at different DR hours and for different duration of time. Figure 5.11 Increasing setpoint by a) 2°C, b) 3°C, and c) 4°C. shows results found for increasing the setpoint by 2°C, 3°C, and 4°C. Figure 5.12 demonstrates results of applying pre-cooling strategy by different degrees and periods in the morning. Figure 5.13, Figure 5.14, and Figure 5.15 respectively present results of reducing air flow rate to 3 kg/s and 1 kg/s, powering off fan, and DCV.

A general analysis of results based on the daily load shape indicate that:

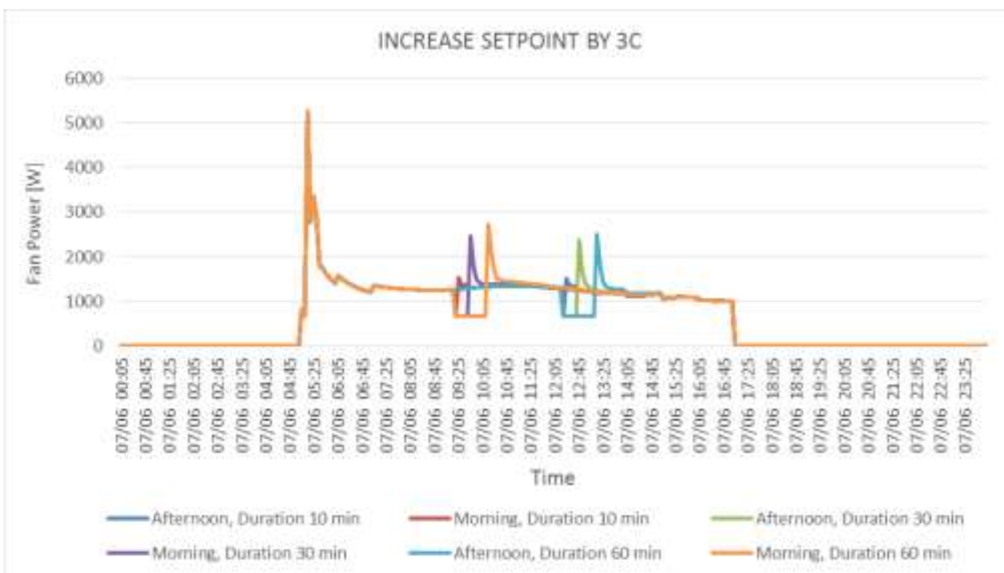
1) Pre-cooling in the morning hours results in a large peak in power consumption without noticeable energy and power reduction in the afternoon hours which are high electricity demand hours.

2) Increasing the setpoint by either 2°C, 3°C, or 4°C does not make much difference in terms of power consumption. In other words, the impact on power demand is the same regardless of if setpoint is increased by 2°C or 4°C. This is because the supply fan reaches its max in all cases.

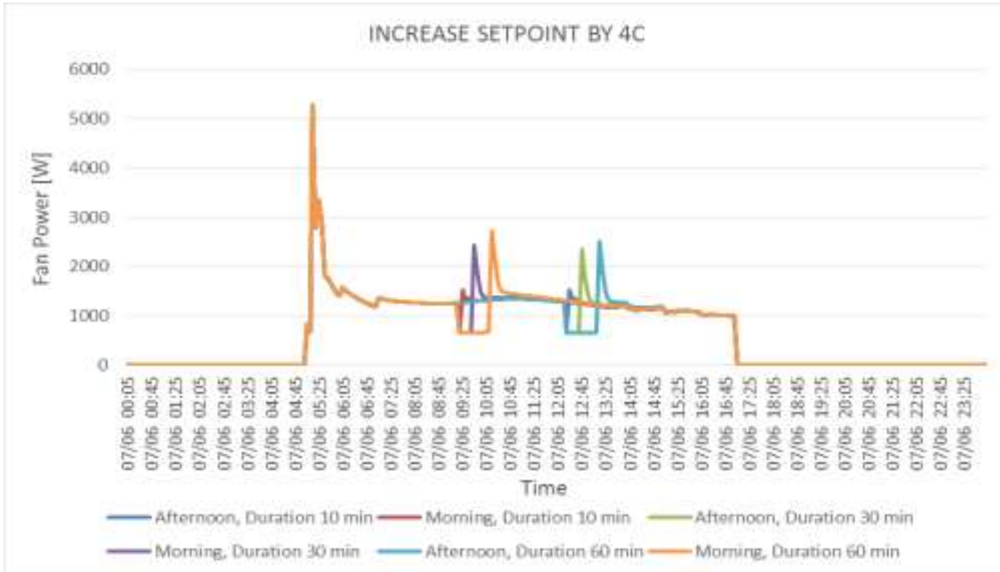
3) Reducing the amount of outdoor air during afternoon hours results in a large rebound after the DR period.


INCREASE SETPOINT BY 2C
Fan Power [W]
Time
Afternoon, Duration 120 min
Morning, Duration 120 min
Afternoon, Duration 30 min
Morning, Duration 30 min
Afternoon, Duration 60 min
Morning, Duration 60 min

(a)


INCREASE SETPOINT BY 3C
Fan Power [W]
Time
Afternoon, Duration 10 min
Morning, Duration 10 min
Afternoon, Duration 30 min
Morning, Duration 30 min
Afternoon, Duration 60 min
Morning, Duration 60 min

(b)




(c)

Figure 5.11 Increasing setpoint by a) 2°C, b) 3°C, and c) 4°C.

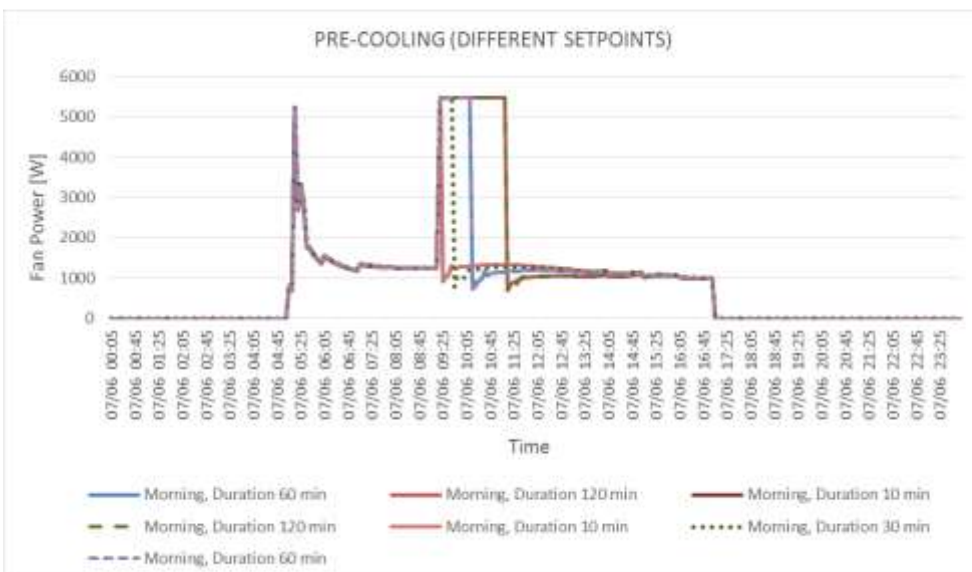
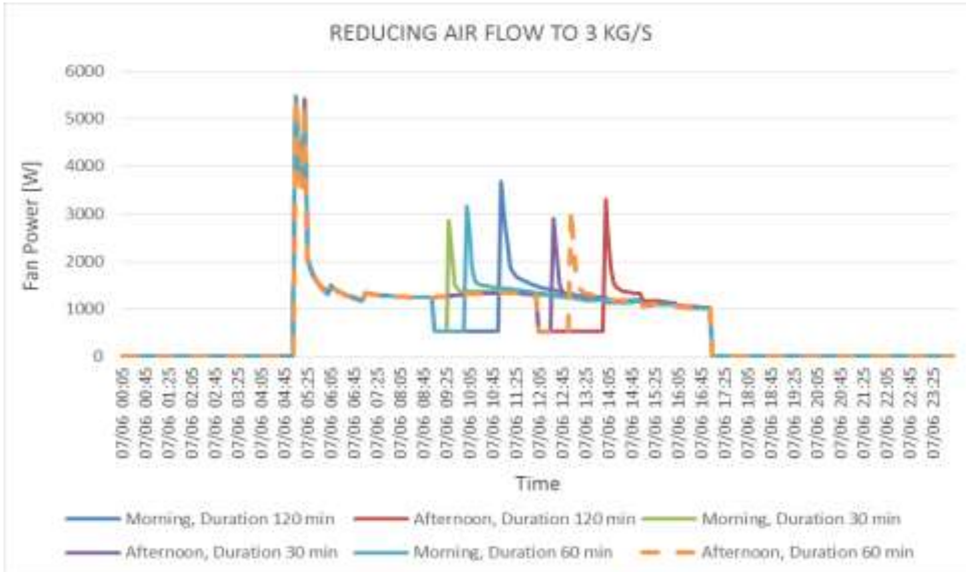
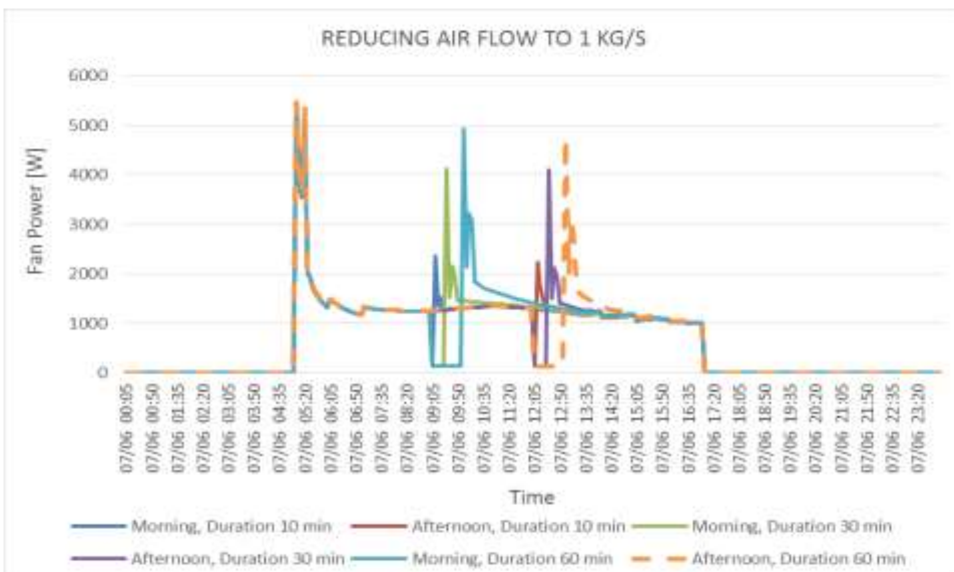



Figure 5.12 Pre-cooling (decreasing setpoint)




(a)




(b)

Figure 5.13 Reducing fan air flow to: a) 3 kg/s and b)1kg/s.

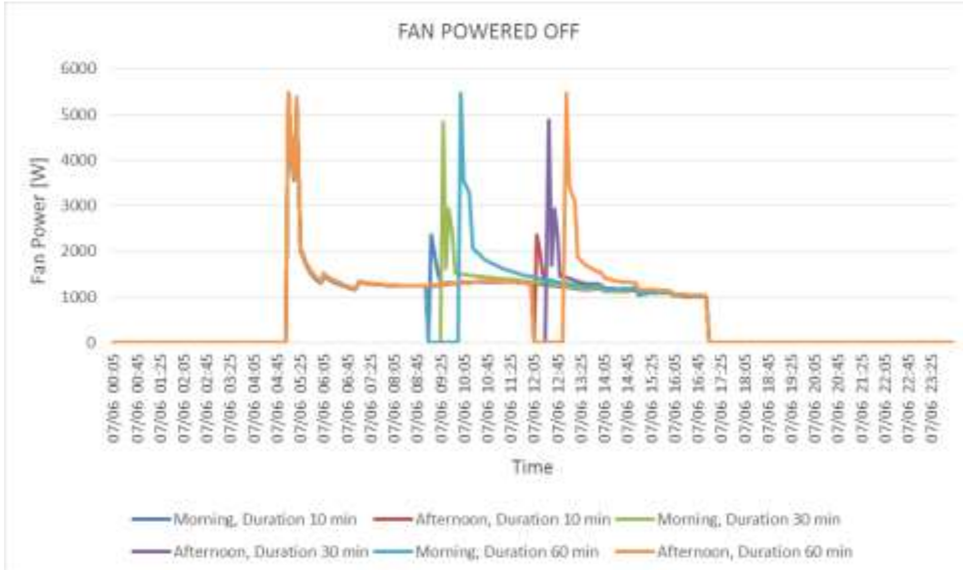



Figure 5.14 Fan powered off.

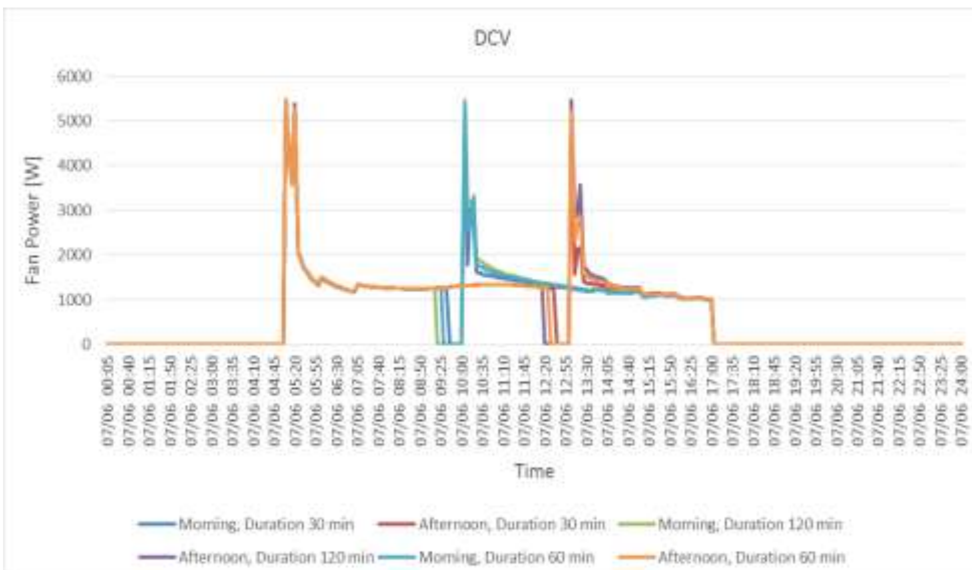



Figure 5.15 Demand control ventilation (reducing OA)

## 5.5 Performance Quantification

Using the outcomes of the simulations, the different PIs defined in the previous chapter are calculated. As it was mentioned earlier, not all PIs defined are applicable to this case study and only those listed in Table 4.1 are applied to measure performance of control strategies to find the most important PIs for system performance assessment in the context of DR. These PIs are measured and ranked per control strategy to conclude which PI's determine how a certain DR control strategy perform against another one.

### 5.5.1 Power Performance

#### 5.5.1.1 *Maximum to Average Power Ratio (MAPR)*

The minimum and maximum power consumption achieved by each control strategy under a given scenario are important when evaluating HVAC control mechanisms for DR. These values are direct indicatives of how much load is deviating from average causing a peak or dip demand. The minimum and maximum demand compared to average are shown in Figure 5.16 and Figure 5.17 respectively. The difference between minimum or maximum power and average demand indicate how flexible the demand or in other words the strategy applied are.

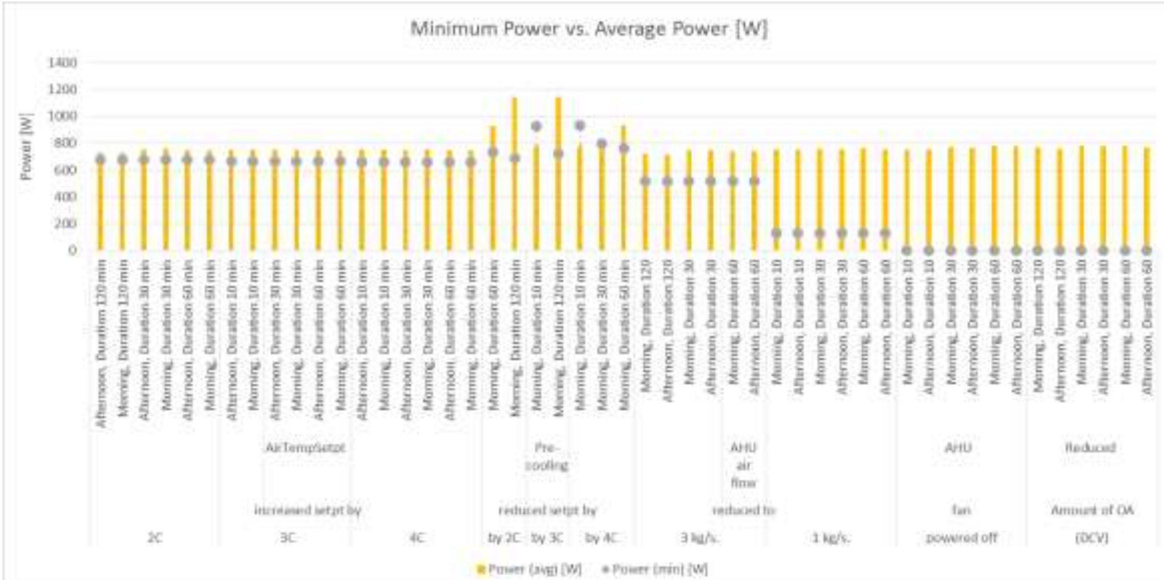



Figure 5.16 Minimum power consumption in one day resulted by each control strategy under different scenarios.

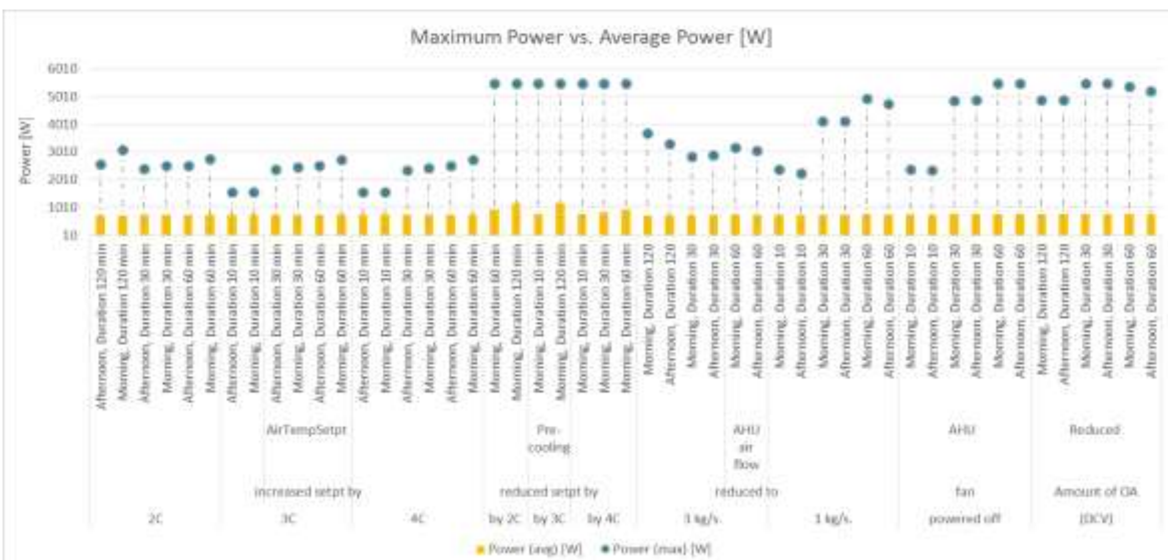



Figure 5.17 Maximum power consumption in one day resulted by each control strategy under different scenarios.

The ratio of maximum to average power consumption as quantified as the first PI (MAPR) indicates: 1) rebound if assessing performance of control strategies (the higher, the higher the rebound), 2) peak and hence flexibility for load reduction if assessing load profile (the higher, the higher the flexibility). Although MAPR can be used to assess the extent (i.e., height) of peak or rebound, it is not a good indicator for the duration of peak. Figure 5.18 through Figure 5.22 illustrate the MAPR of the fan under different control scenarios. Result indicate that a larger value of MAPR means larger (i.e., taller) peak or rebound. Figure 5.18 illustrates MAPR of the supply fan when the setpoint is increased for different durations of DR. Results indicate that the value of MAPR remains the same (i.e., the length of a peak or rebound is the same) if setpoint is increased by 2ºC, 3ºC, or 4ºC. However, the longer the duration of DR, the higher the value of MAPR. Increasing the setpoint for a duration of 120 minutes in the morning (blue line) results in higher peak compared to if setpoint is increased in the afternoon (red line).

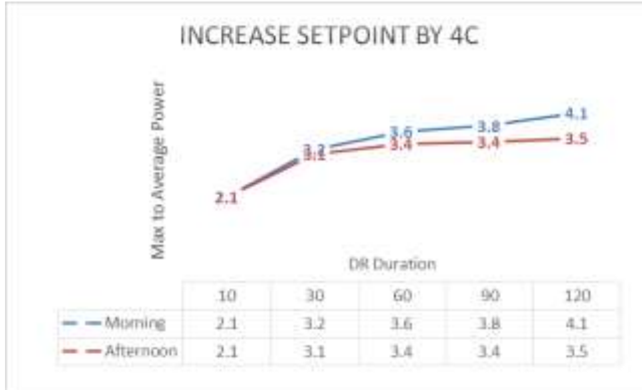




Figure 5.18 Performance of the system in terms of MAPR for different durations [minutes] of DR when setpoint changes (increase).

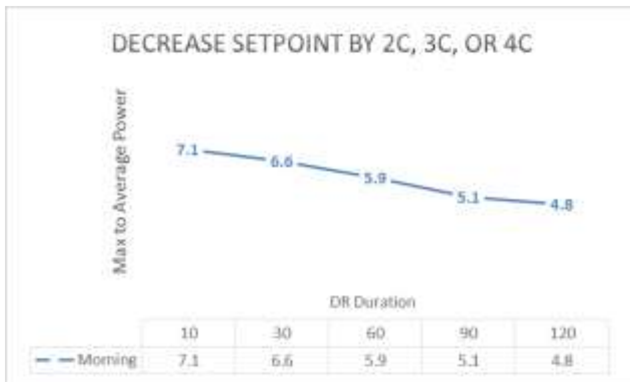



Figure 5.19 Performance of the system in terms of MAPR for different durations [minutes] of DR when setpoint changes (pre-cooling).

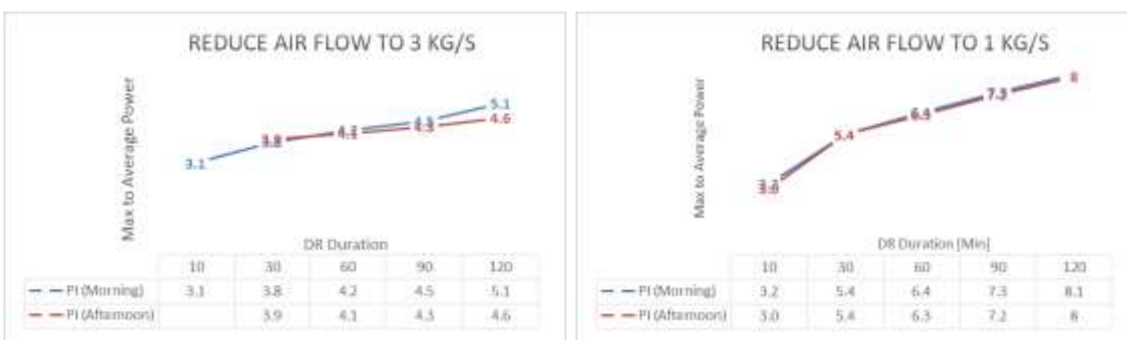



Figure 5.20 Performance of the system in terms of MAPR for different durations [minutes] of DR when air flow is reduced to: left) 3 kg/s and right) 1 kg/s.

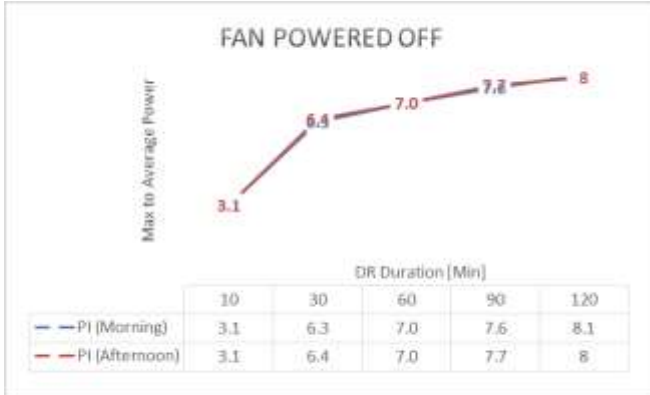



Figure 5.21 Performance of the system in terms of MAPR for different durations [minutes] of DR when fan is powered off.

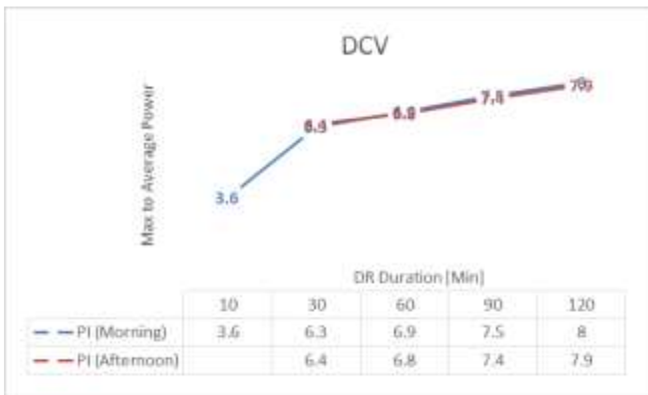



Figure 5.22 Performance of the system in terms of MAPR for different durations [minutes] of DR when DCV is applied.

#### 5.5.1.2 *Load Disparity Coefficient*

A smaller value indicates less deviation from average load. Two ways to use:

1) Evaluate normal load -> if load disparity is closer to 1 or above 1, it has potential for peak management
2) Evaluate DR strategies -> if load disparity is closer to 0, the strategy used is a more ideal one because it causes less deviation from average demand and less rebound effect.

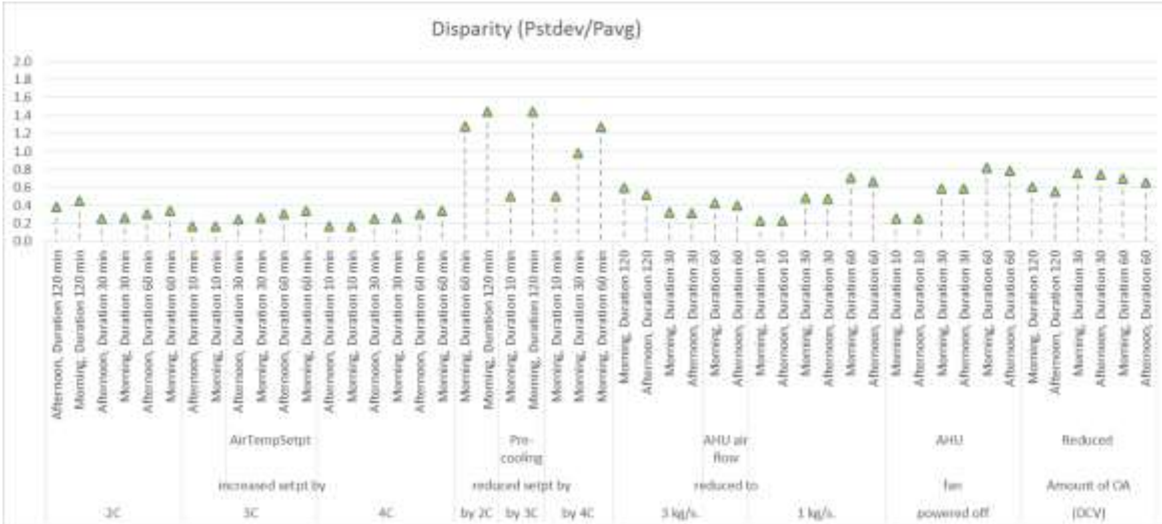
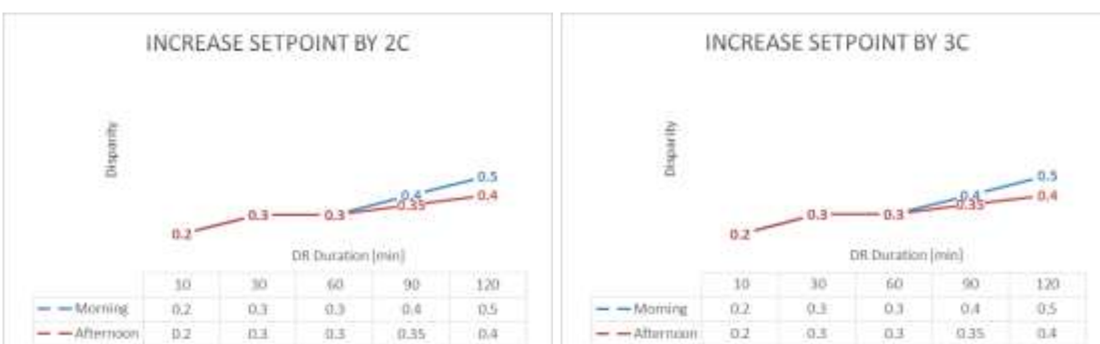



Figure 5.23 Load disparity in one day for each scenario.

Figure 5.24 through Figure 5.28 illustrate load disparity of the supply fan under different control scenarios. The higher the load disparity, the higher and longer the peak or rebound is. For instance, Figure 5.25 shows load disparity of the supply fan when the setpoint is increased for different durations of DR. Results indicate that disparity remains the same (i.e., the length and duration of a peak or rebound is the same) if setpoint is increased by 2ºC, 3ºC, or 4ºC. However, increasing the setpoint for a duration of 120 minutes in the morning (blue line) result in higher peak compared to application in the afternoon (red line).



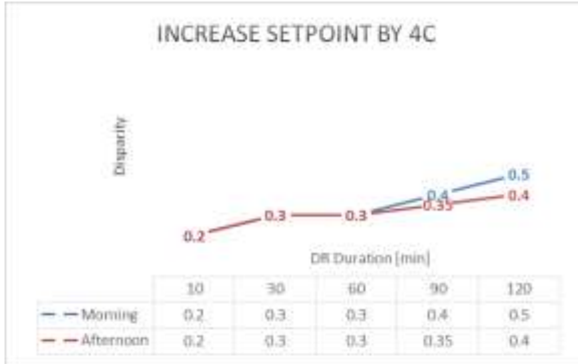



Figure 5.24 Performance of the system in terms of demand disparity for different durations [minutes] of DR when setpoint changes (increase).

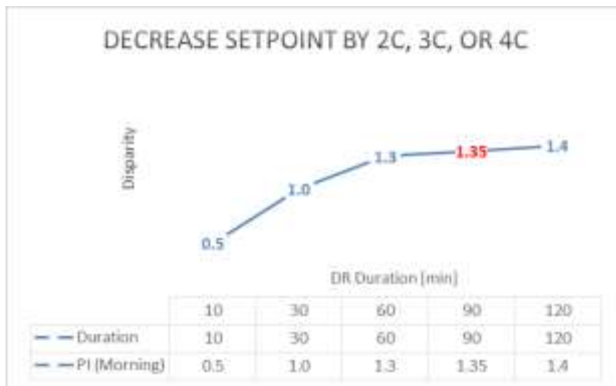



Figure 5.25 Performance of the system in terms of demand disparity for different durations [minutes] of DR when setpoint decreases (pre-cooling).

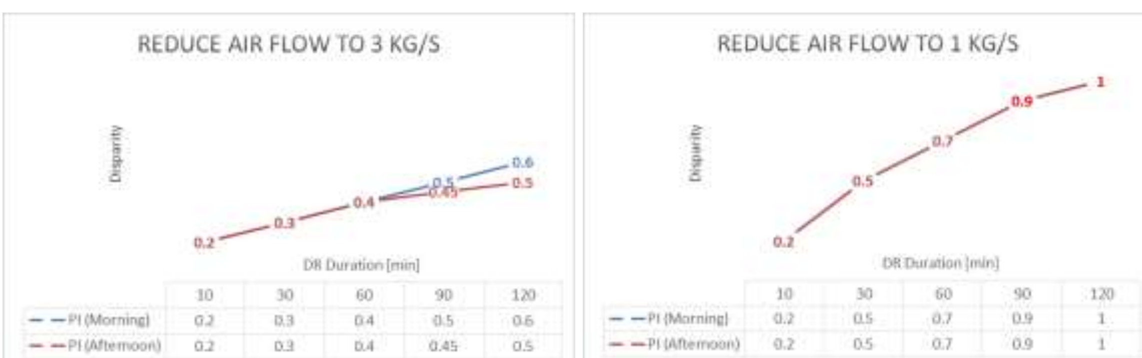



Figure 5.26 Performance of the system in terms of demand disparity for different durations [minutes] of DR when air flow is reduced to 3 kg/s and 1kg/s.


Figure 5.27 Performance of the system in terms of demand disparity for different durations [minutes] of DR when fan is powered off.

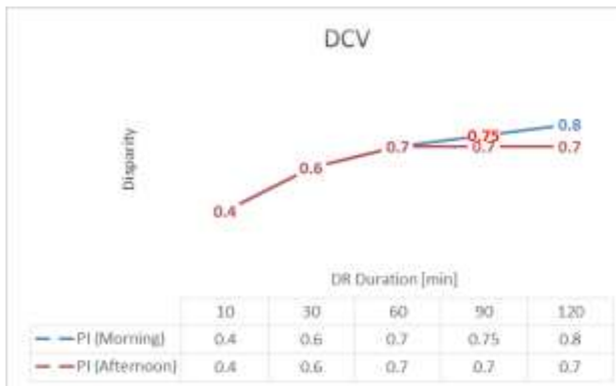



Figure 5.28 Performance of the system in terms of demand disparity for different durations [minutes] of DR when OA is reduced.

#### 5.5.1.3 *Load or Power Intensity*

Load intensity was defined as power per unit of time per unit of space (e.g., W/(5min)/m$^2$). This is a time-series measurement and data should be collected and assessed at a given time step. In this case study, the building power performance was simulated every 5 minutes. Therefore, power is divided by the area of all zones served by AHU1 at each 5-minute time interval to calculate load intensity. The total area served by AHU1 is 1295 m$^2$.

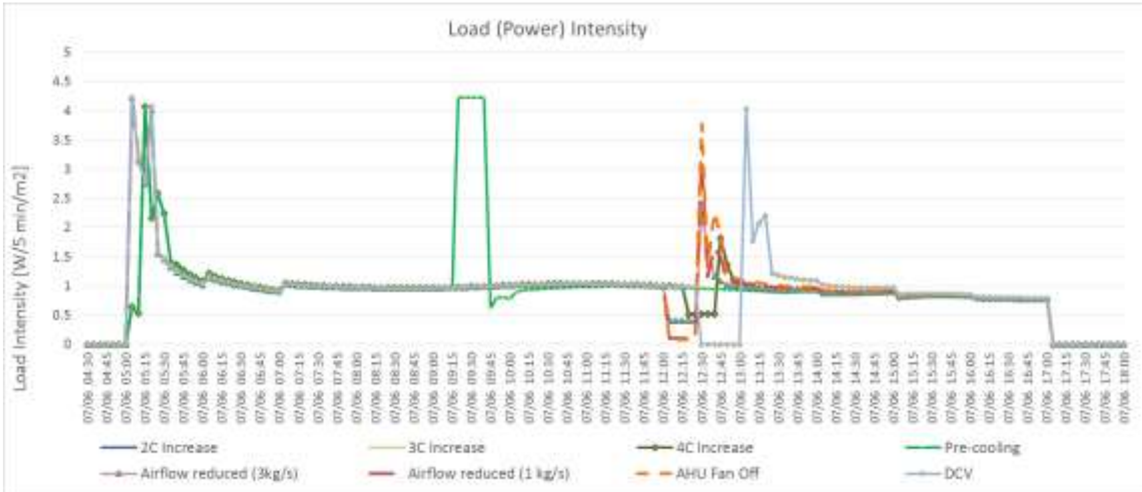



Figure 5.29 Load (power) intensity calculated at each time step for a set of control strategies. DR duration is 30 minute in the afternoon except for pre-cooling.

The applicability of this PI is limited in this case because only one zone and one building was considered. Load intensity is a way to normalize power consumption to have a comparable value when evaluating power use of a building or zone against another.

#### 5.5.1.4 *Power Performance Coefficient (PPC)*

PPC is the ratio of average or median power in a given time period (one day in this case study) to power consumption at the current timestep (or any instance of time the performance is being assessed). Therefore, this is also a time series calculation which should be carried out at every time interval to make informed decision about HVAC operation at that time for the next time interval. For instance, in this case study, PPC is calculated every five minutes.

If analyzing the load profile, having PPC below one means that the load is peaking and hence flexible to participate in DR, peak management, or load reduction to conserve energy. If analyzing power performance of a system in presence of a set of control strategies to select the most applicable mechanism, having a PPC equal or close to one means the strategy is ideal but as it gets closer to zero (PPC<1), it means current power consumption is getting larger than average, which indicates rebound shaping. As PPC gets larger (PPC>1), it means current power use is smaller than average consumption. This is not a concern if the goal is to conserve energy, however, any deviation from average power consumption means stress to the power system.

In the sample selected for illustration (shown in Figure 5.30), reducing airflow to 1 kg/s and shutting down the fan result in a large PPC because the fan energy consumption gets very close to zero or becomes zero. DCV and pre-cooling have the lowest PPC. This suggests presence of a large rebound after DR period. PPC is a good indicator of load dipping.

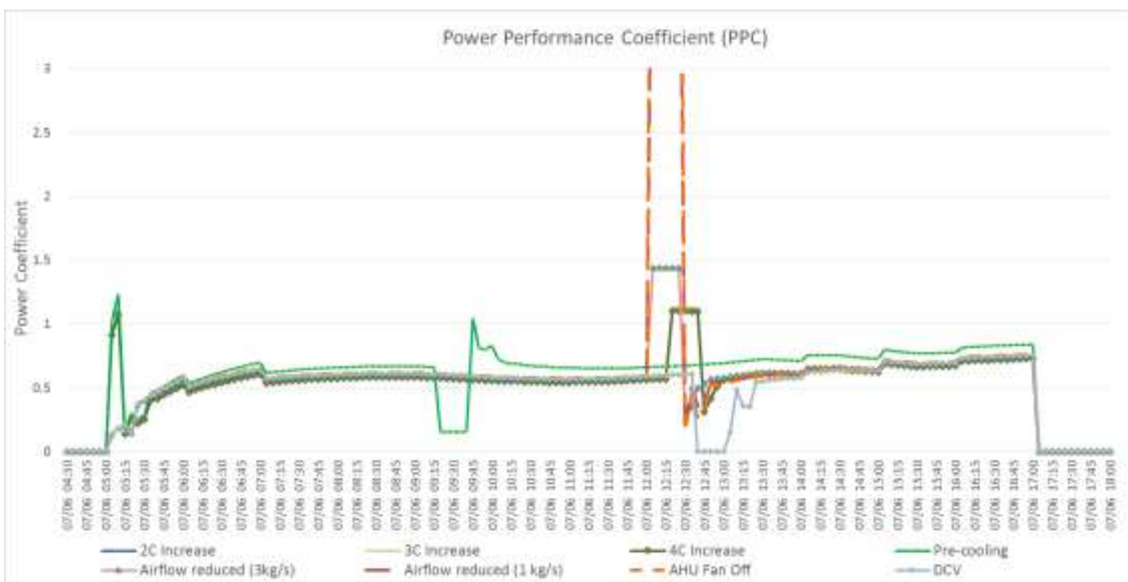



Figure 5.30 Ratio of average power to current power consumption calculated at each time step for a set of control strategies. DR duration is 30 minute in the afternoon except for pre-cooling, which is implemented in the morning for 30 minutes.

Although PPC is more meaningful when calculated in time series, here averages in one day are taken for each strategy in order to have comparable results with other PIs. Figures Figure 5.31 through Figure 5.35 illustrate load PPC of supply fan under different control scenarios. As expected an average PPC is not well descriptive of behavior of load. However, it well presents existence of big load drops or dips.

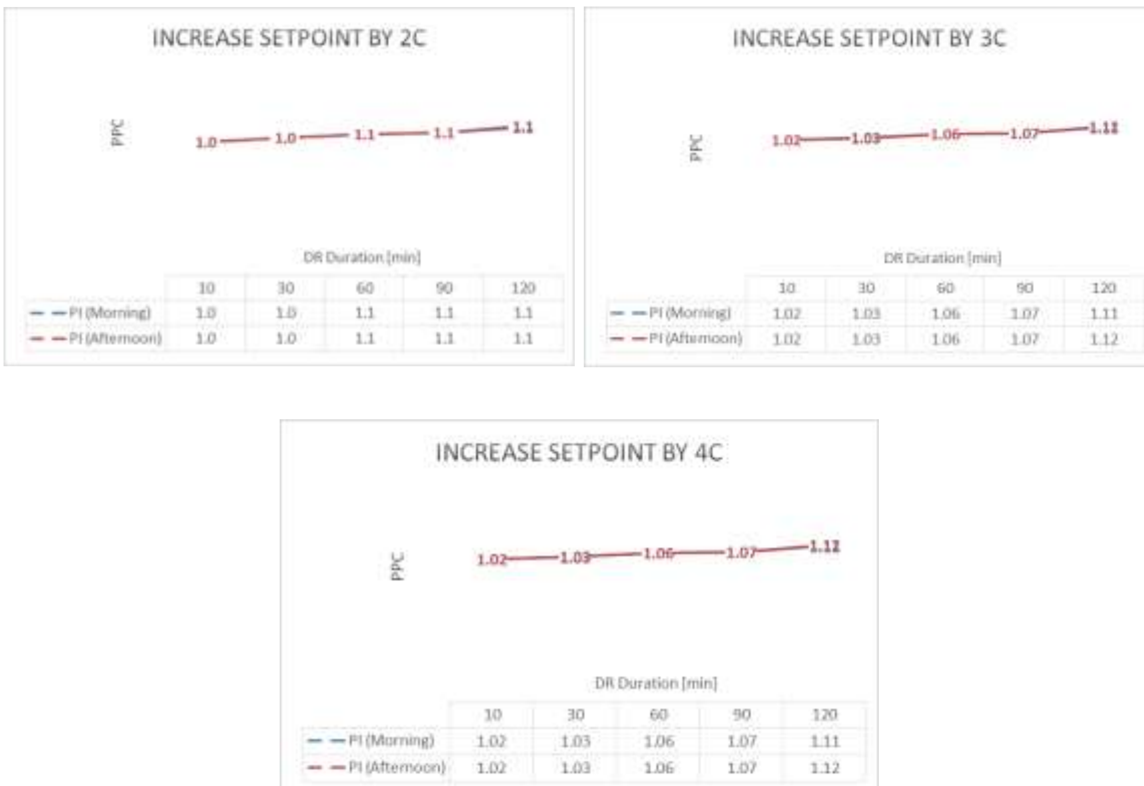



Figure 5.31 Performance of the system in terms of PPC for different durations [minutes] of DR when setpoint changes (increases).

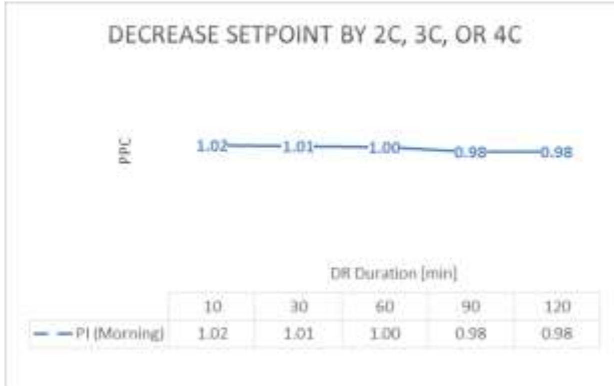



Figure 5.32 Performance of system in terms of PPC for different durations [minutes] of DR when setpoint decreases (pre-cooling).

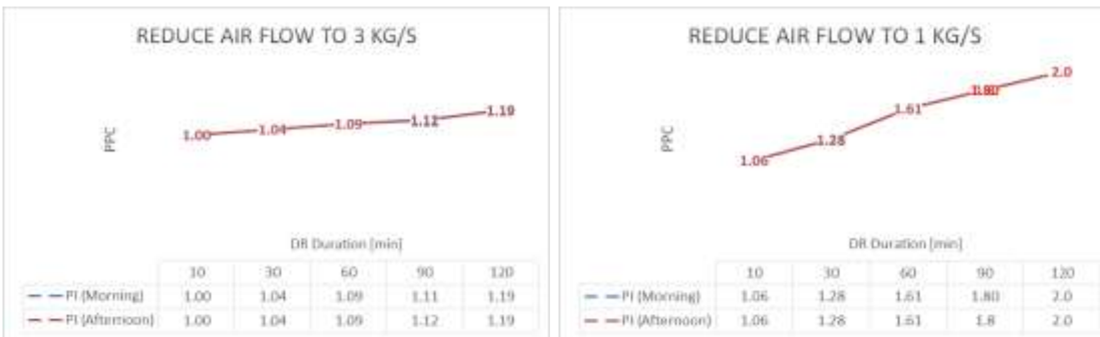



Figure 5.33 Performance of system in terms of PPC for different durations [minutes] of DR when air flow reduces to 3 kg/s or 1 kg/s.

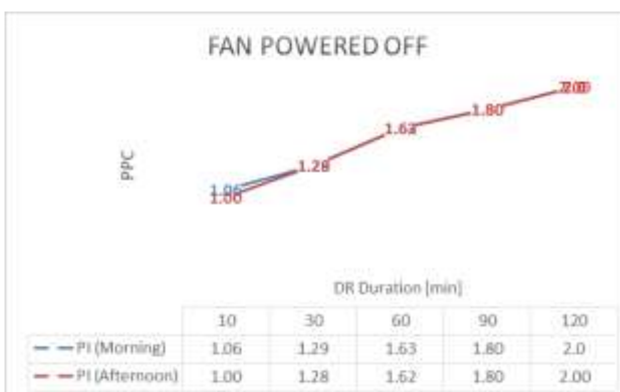



Figure 5.34 Performance of system in terms of PPC for different durations [minutes] of DR when fan is powered off.


Figure 5.35 Performance of system in terms of PPC for different durations [minutes] of DR when amount of OA is reduced.

### 5.5.2 Energy Performance

One of the most emphasized concerns about DR and power efficiency is its trade-off with energy efficiency. Hence, it is important to take into account the energy consumption of systems when different control strategies are applied for each DR scenario. Figure 5.36 illustrates a summary of energy consumption of the AHU fan in one day for different scenarios implemented. The energy consumption of the base case (without any control strategy applied during DR) is about 16 kWh/day. Results presented indicate that the AHU consumes about the same amount of energy in most scenarios implemented except for pre-cooling strategies, which consume more energy especially if implemented for more than 10-30 minutes in the morning. Increasing setpoint by 2°C for 120 minutes results in the lowest energy consumption (*note: increasing setpoint by 3 or 4°C were only implemented for shorter periods of DR)*.

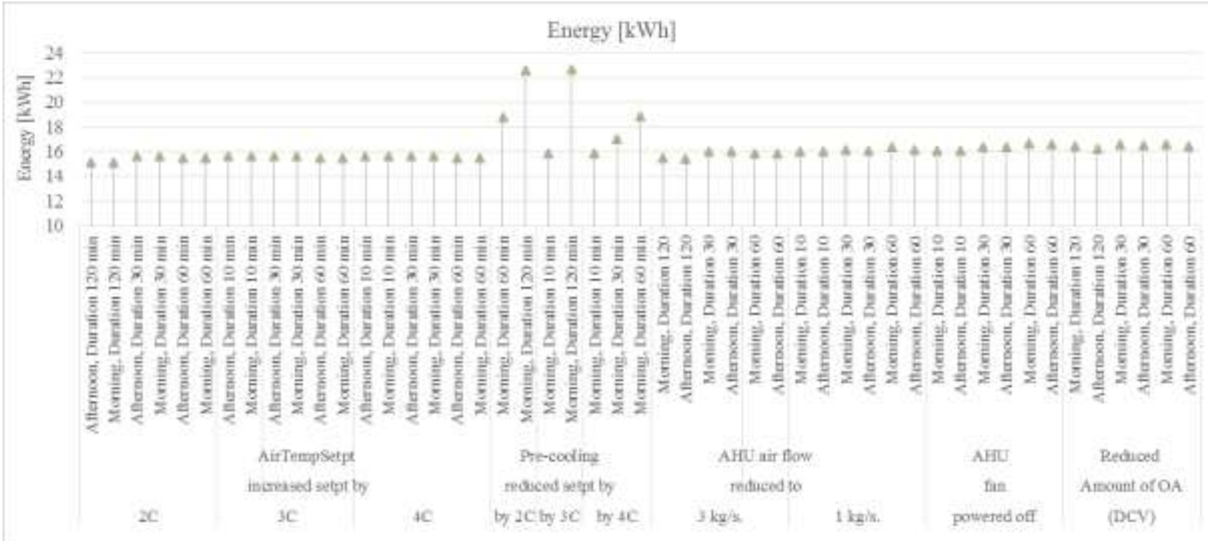



Figure 5.36 Performance assessment of different strategies in terms of energy use in one day.

Figure 5.36 through Figure 5.41 illustrate energy performance of supply fan under different control scenarios. The energy consumption is calculated for one day to measure how performance of the system compare from one control space to another one. For instance, Figure 5.36 shows energy consumption of the supply fan when setpoint is increased for different durations of DR. Results indicate that energy consumption remains the same if setpoint is increased by 2ºC, 3ºC, or 4ºC. However, increasing setpoint for a duration of 120 minutes in result in lower energy consumption compared to lower duration of DR.

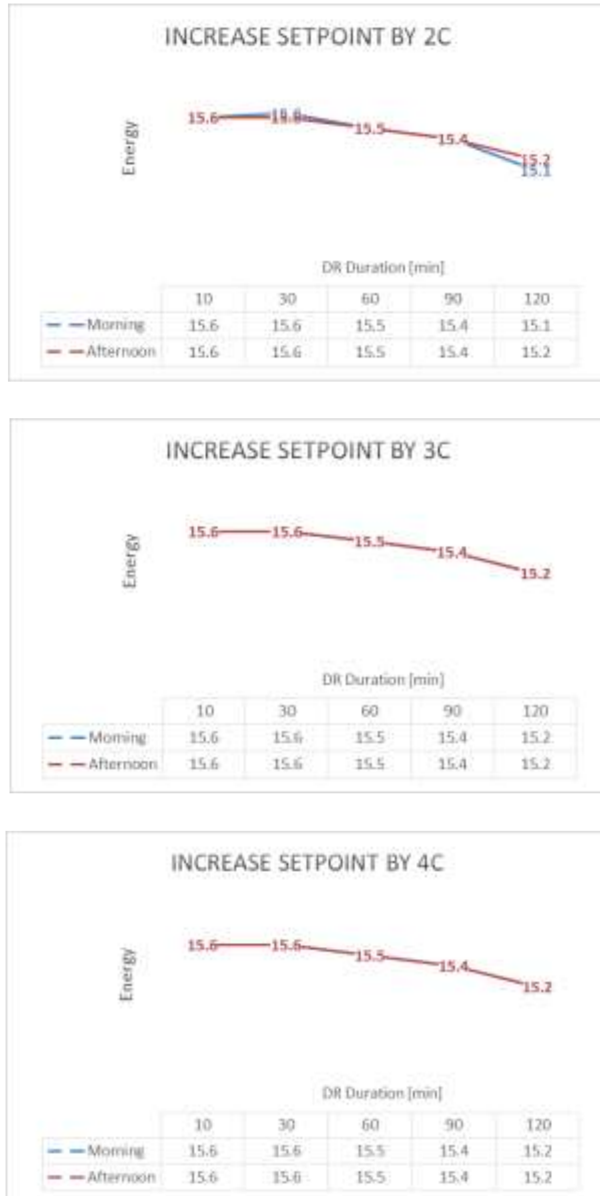



Figure 5.37 Performance of the system in terms of energy use for different durations [minutes] of DR when the setpoint increases.

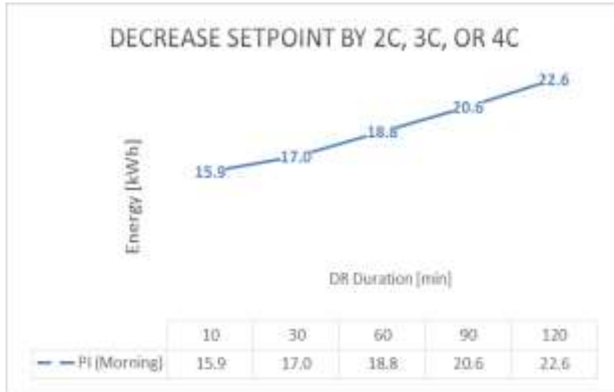



Figure 5.38 Performance of the system in terms of energy use for different durations [minutes] of DR when the setpoint is reduced (pre-cooling).

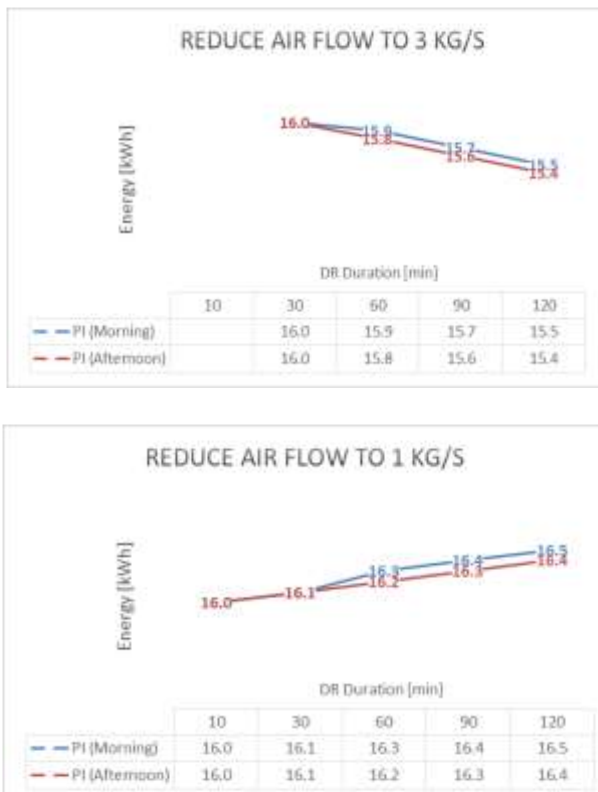



Figure 5.39 Performance of the system in terms of energy use for different durations [minutes] of DR when air flow is reduced to 3 kg/s and 1kg/s.

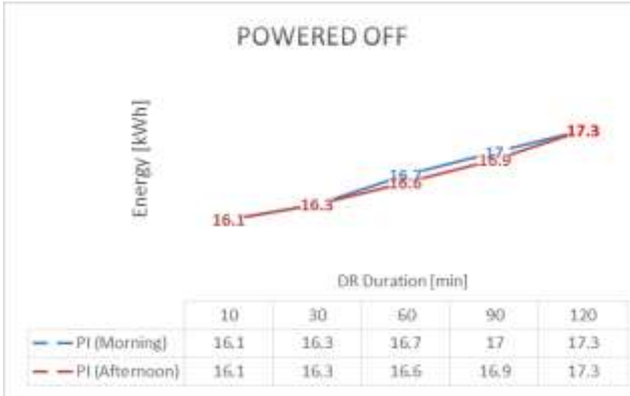



Figure 5.40 Performance of the system in terms of energy use for different durations [minutes] of DR when supply fan is powered off.

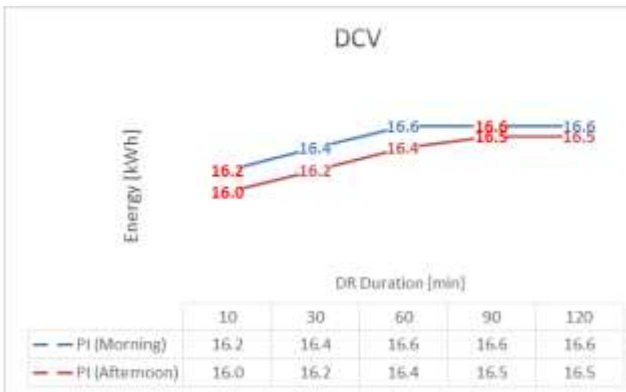



Figure 5.41 Performance of the system in terms of energy use for different durations [minutes] of DR when OA is reduced.

### 5.5.3 Thermal Comfort

Thermal comfort is assessed in terms of two indicators. One is the duration of zone temperature deviating from setpoint temperature and the second is the magnitude of space temperature varying from setpoint. A few strategies were selected to illustrate their performance in terms of temperature variation (Δ**T**) and results are shown in Figure 5.42. Based on results obtained, shutting off AHU fan or applying DCV cause the maximum variation from setpoint temperature followed by reducing air flow and pre-cooling.

Considering absolute (ΔT) provides a more robust and comparable outcome especially if results are to be used in an automated energy and power management systems.

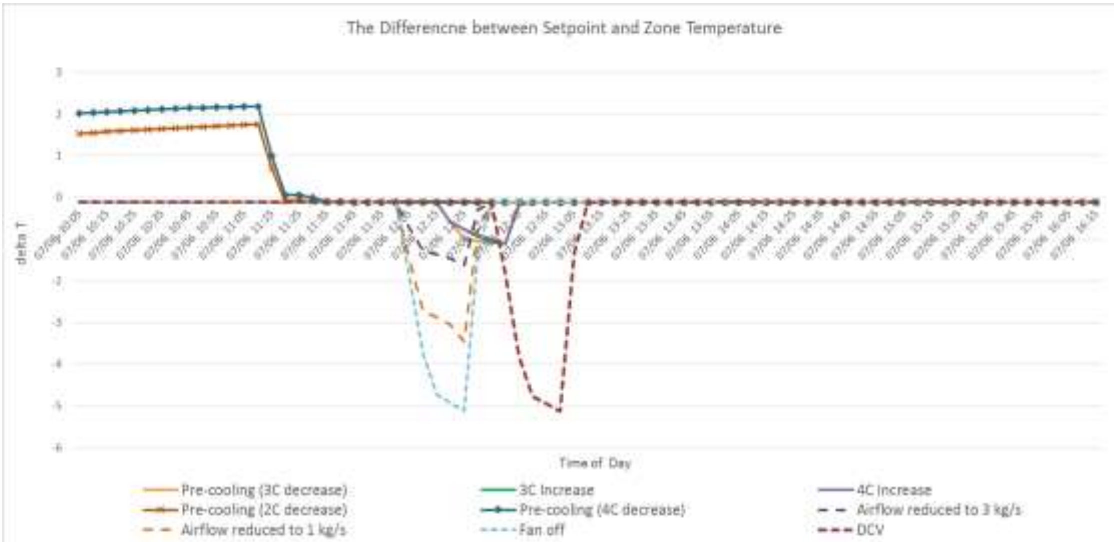
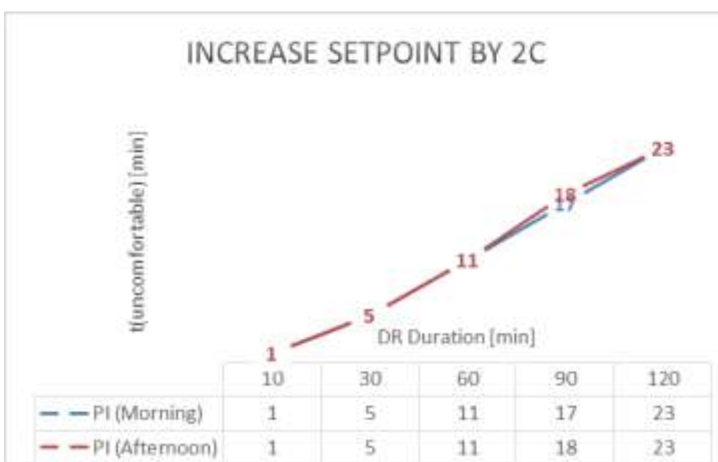
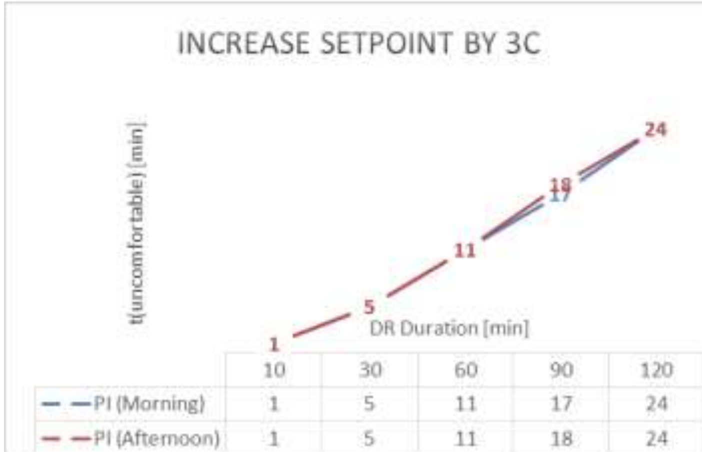



Figure 5.42 The difference between setpoint and zone temperature for control strategies implemented. DR duration is 30 minute in the afternoon except for pre-cooling.

Figure 5.36 through Figure 5.47 illustrate duration of space temperature deviating from setpoint temperature when different control scenarios implemented. These values representing the duration of temperature not being comfortable are found for one day.





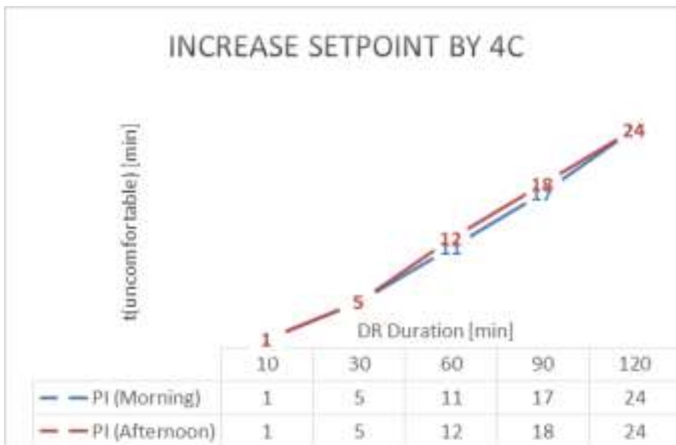




Figure 5.43 Performance of the system in terms of the length of uncomfortable minutes for different durations [minutes] of DR when the setpoint is increased by 2, 3, or 4ºC.

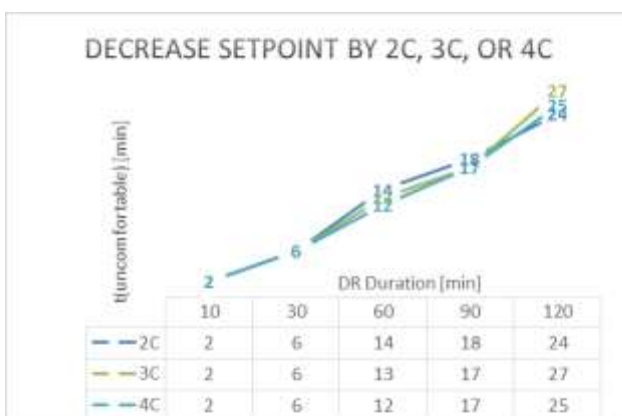



Figure 5.44 Performance of the system in terms of the length of uncomfortable minutes for different durations [minutes] of DR when the setpoint reduced by 2, 3, or 4ºC.

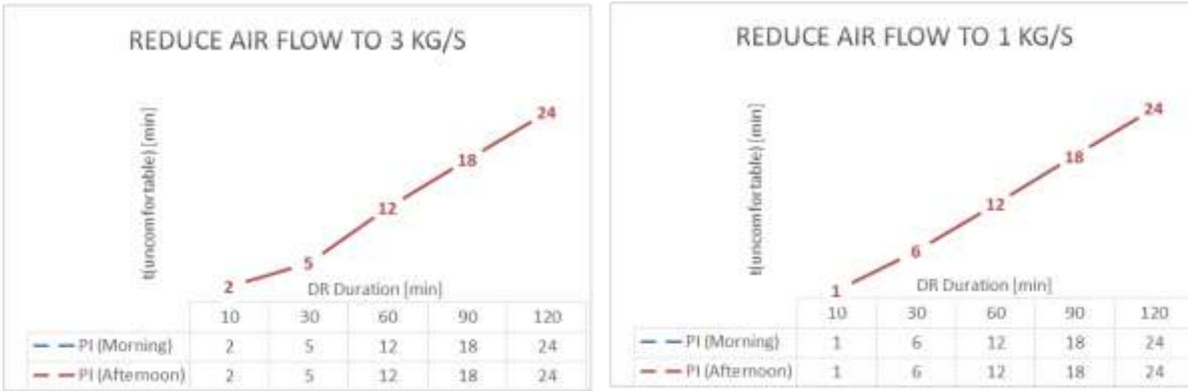



Figure 5.45 Performance of the system in terms of the length of uncomfortable minutes for different durations [minutes] of DR when air flow is reduced to 3 or 1 kg/s.

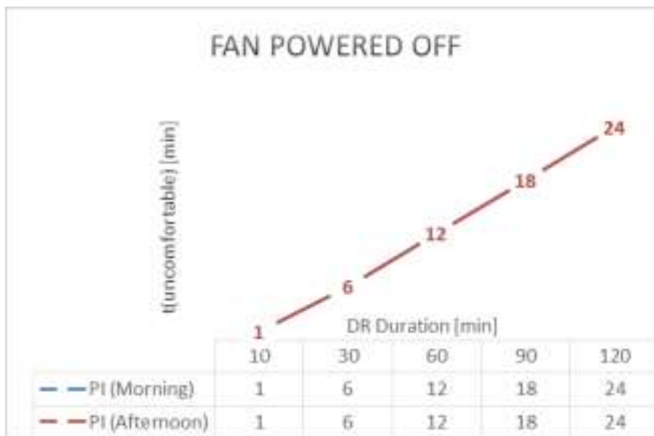



Figure 5.46 Performance of the system in terms of the length of uncomfortable minutes for different durations [minutes] of DR when fan is powered off.

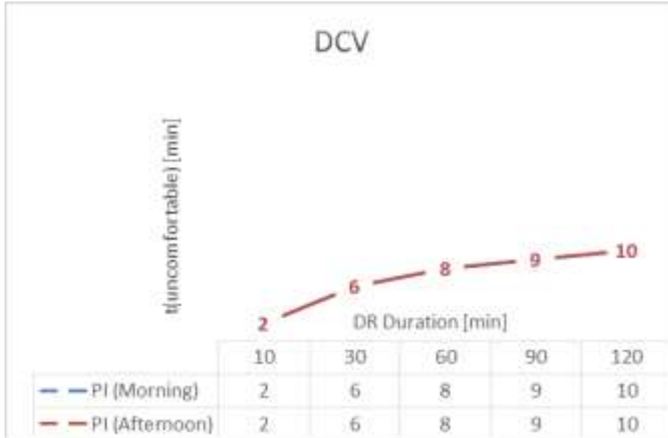
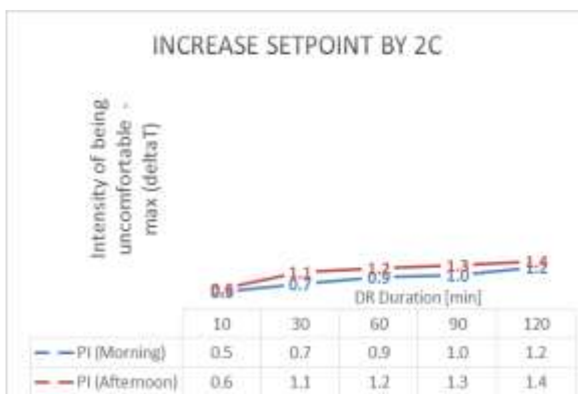
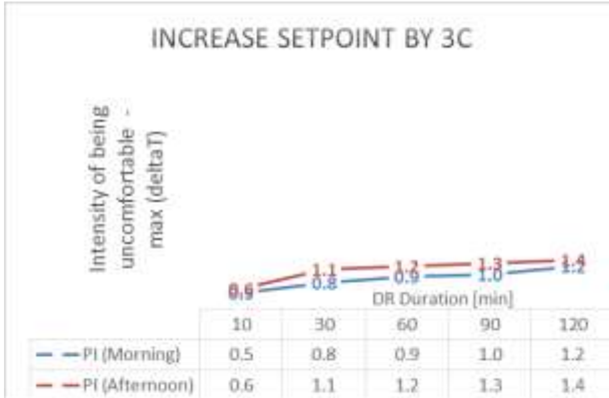



Figure 5.47 Performance of the system in terms of the length of uncomfortable minutes for different durations [minutes] of DR when OA is reduced.

Figure 5.48 through Figure 5.47Figure 5.52 illustrate the magnitude of a space temperature deviating from the setpoint temperature when different control scenarios implemented. The values shown are the maximum temperature difference found in one day.





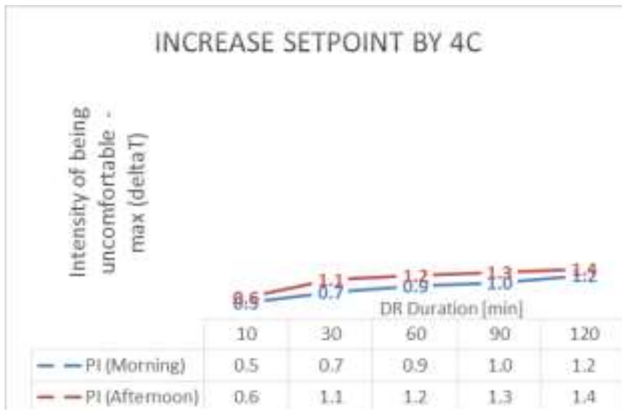




Figure 5.48 Performance of the system in terms of intensity of uncomfortable temperature for different durations [minutes] of DR when setpoint is increased by 2, 3, or 4ºC.

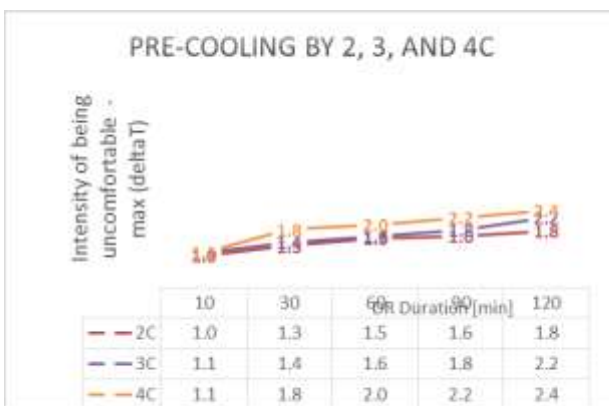



Figure 5.49 Performance of the system in terms of intensity of uncomfortable temperature for different durations [minutes] of DR when setpoint is reduced by 2, 3, or 4ºC.

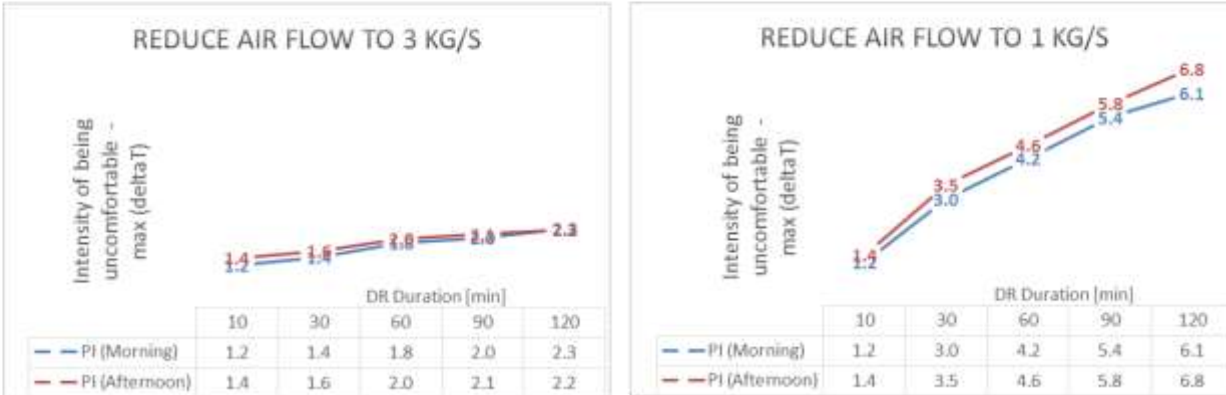



Figure 5.50 Performance of the system in terms of intensity of uncomfortable temperature for different durations [minutes] of DR when air flow is reduced to 3 or 1 kg/s.

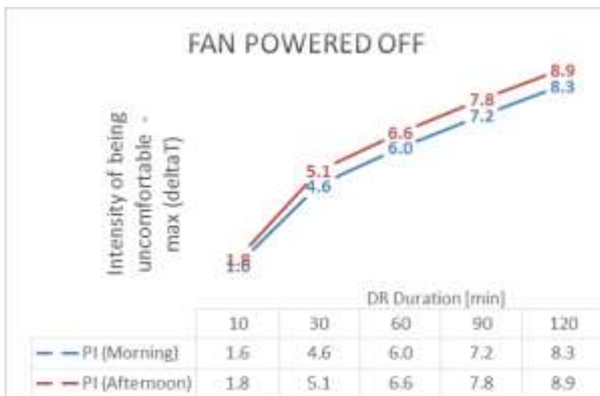



Figure 5.51 Performance of the system in terms of intensity of uncomfortable temperature for different durations [minutes] of DR when fan is powered off.

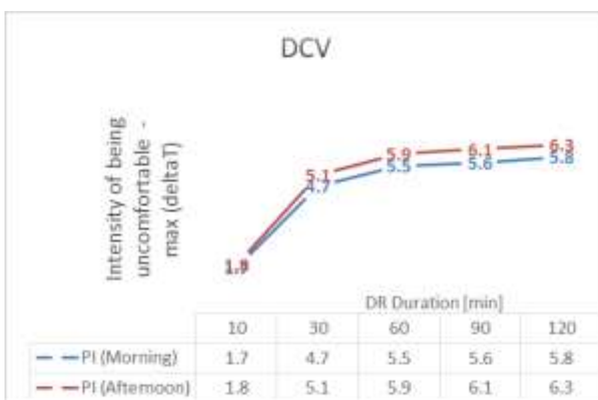



Figure 5.52 Performance of the system in terms of intensity of uncomfortable temperature for different durations [minutes] of DR when OA is reduced.

## 5.6 PIs' Verification

Although PIs were selected and defined carefully with the objective of measuring power, energy, and comfort performance of building energy systems in an effective and meaningful manner, this cannot be verified without quantifying them. Quantification of PIs defined supports two purposes. First, the quantified results can be used to verify appropriateness or effectiveness of PIs selected to answer questions such as 'why these PIs?' and 'which PIs to keep or eliminate?' Second, they can be used to compare performance of one alternative or option against another one. Verification of appropriateness of PIs is discussed in this section and how their quantification support decision making by enabling the comparison of different control strategies and selecting the one that results in the 'best' outcome is discussed in the following section.

The profile or trend of PIs were investigated to assure they do not exhibit the same pattern. Figure 5.53 illustrates an example of how this was accomplished. As it is shown, MAPR and disparity have the same pattern in most cases, yet they do not follow each other all the time. The exhibit different behavior (even inverse pattern) in cases when duration of peak is long. Some measures such as load factor (discussed earlier in section 4.5.1) were not considered for the same reason. Figure 5.54 shows how load factor has exactly an inverse pattern of MAPR.

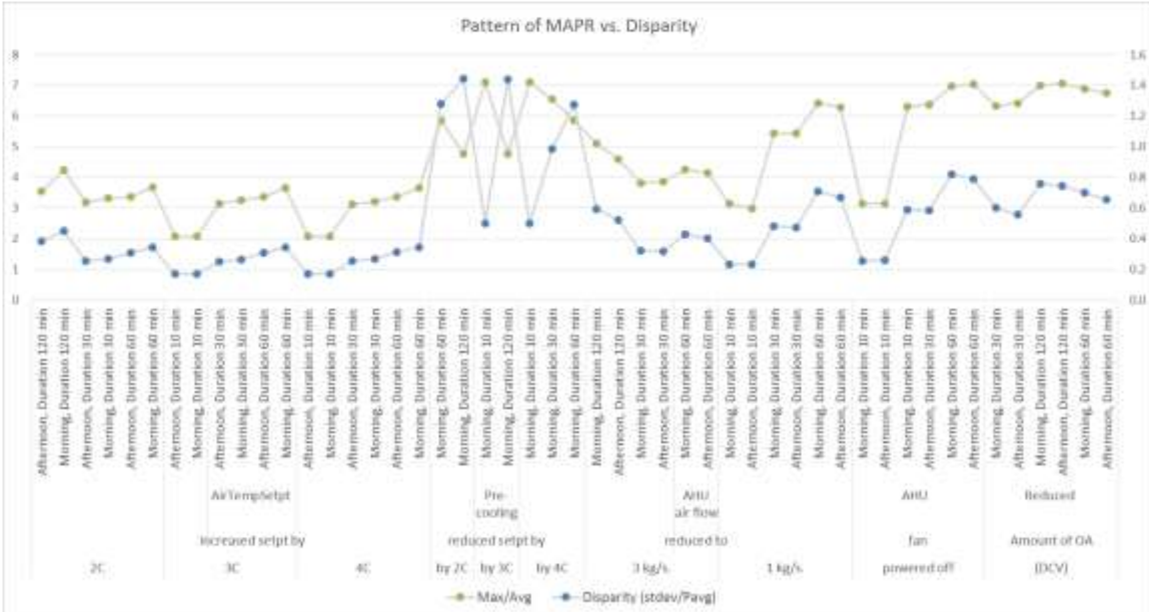



Figure 5.53 Pattern of MAPR vs disparity.

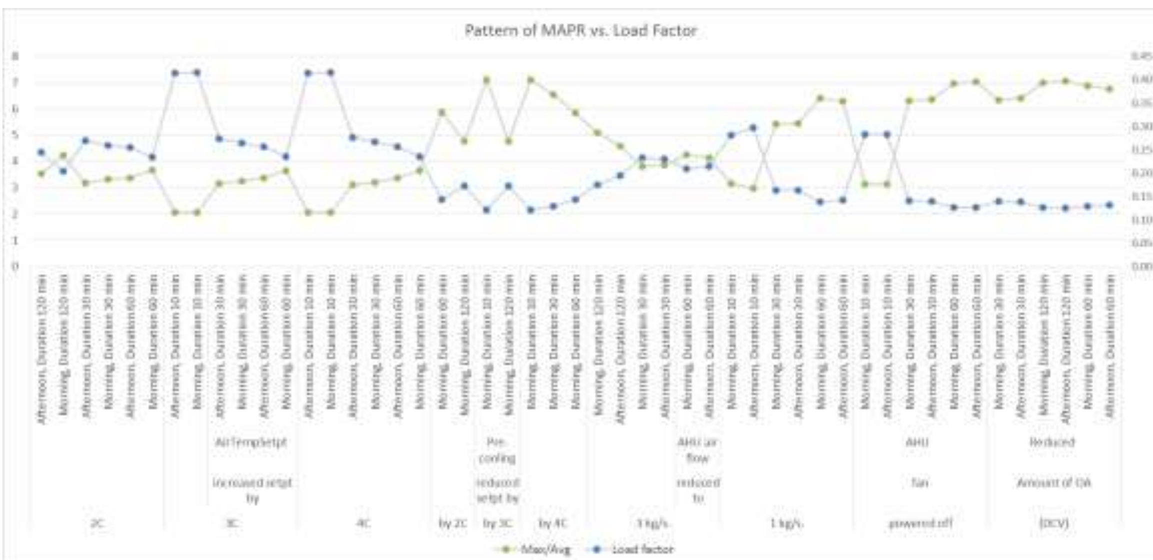



Figure 5.54 Pattern of MAPR vs load factor.

Results normalized and shown in Figure 5.56 to Figure 5.61 depict how performance of different scenarios defined for each category of control strategies compare against each other. For instance in Figure 5.56, quantity of PIs are shown for scenarios related to setpoint increase. *Note:* It was observed that increasing the setpoint by 2, 3, or 4 ºC does not make much difference in terms of value of PIs (see Figure 5.18, Figure 5.24, Figure 5.37, Figure 5.43, and Figure 5.49), hence, outcomes are merged for performance comparison of scenarios related setpoint increase. Normalized outcomes presented also specify effectiveness of each PI in measuring different criterion because results are scattered across PIs and they do not overlap. Figure 5.55 shows definition of nomenclatures used in scalar charts.

Strategies:

S1: Increasing setpoint (since increasing setpoint by 2, 3, or 4 ºC has produced the same results, they are combined as one strategy)
S2: Decreasing setpoint or pre-cooling (since decreasing setpoint by 2, 3, or 4 ºC has produced the same results, they are combined as one strategy)
S3: Reducing air flow to 3 kg/s
S4: Reducing air flow to 1 kg/s
S5: Fan powered off
S6: DCV

PIs:

PI1: MAPR
PI2: Disparity
PI3: PPC
PI4: Energy use
PI5: Thermal comfort (duration of uncomfortable minutes)
PI6: Thermal comfort (intensity of uncomfortable temperature)

Durations:

D1: 10 minutes
D2: 30 minutes
D3: 60 minutes
D4: 90 minutes
D5: 120 minutes

Figure 5.55 Definition of nomenclature used in radar charts shown.

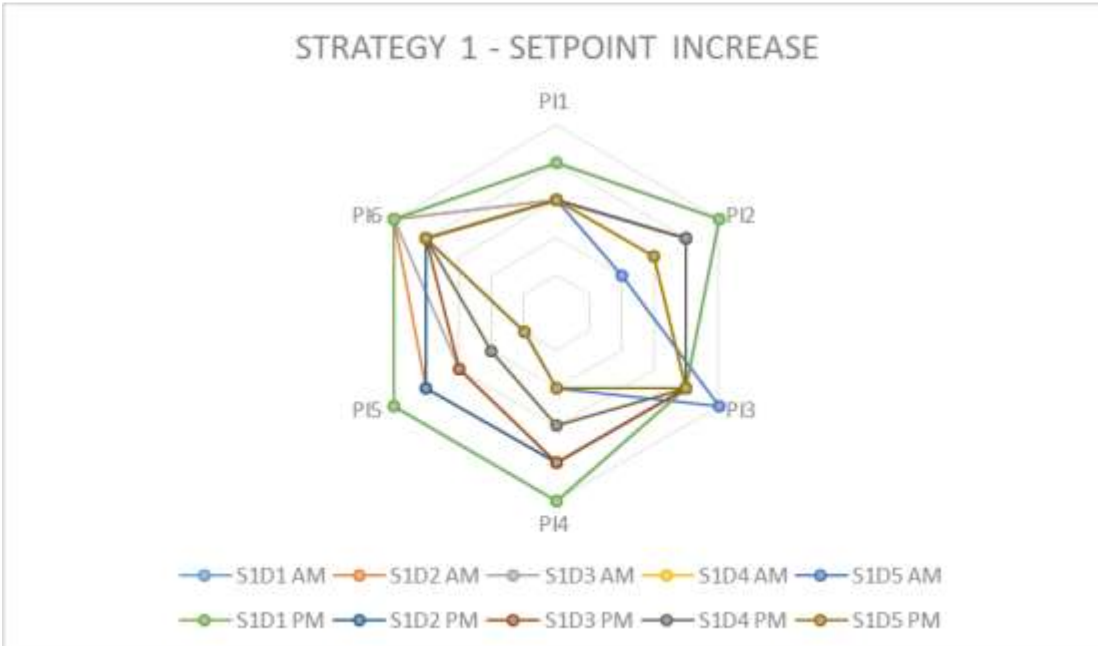



Figure 5.56 Performance comparison of different control scenarios related to setpoint increase.

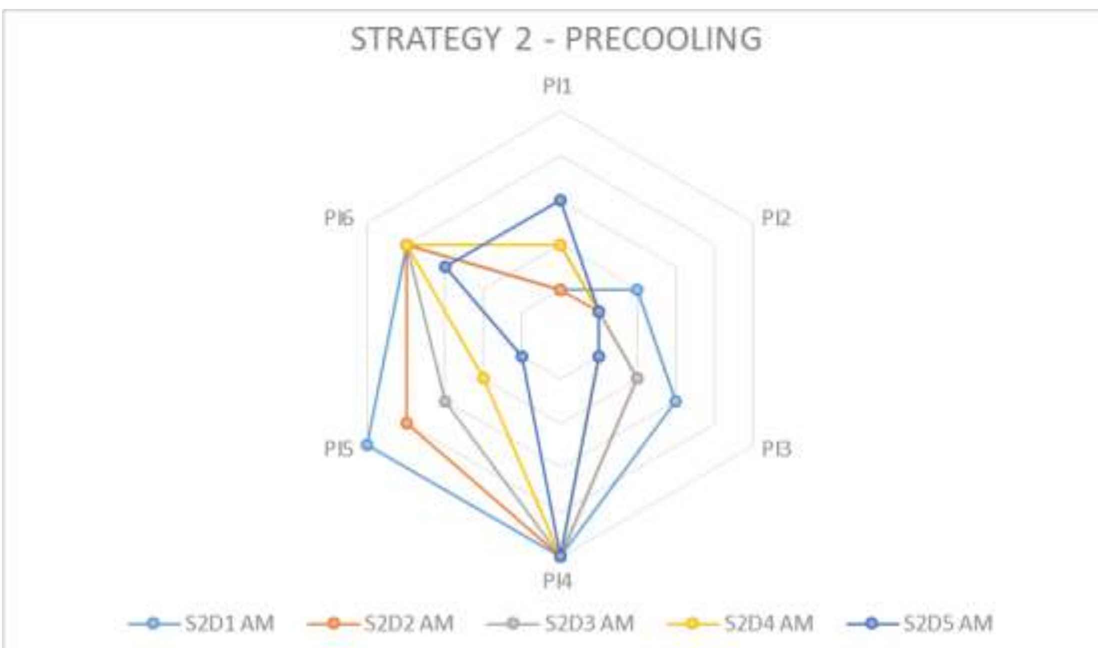



Figure 5.57 Performance comparison of different control scenarios related to pre-cooling.

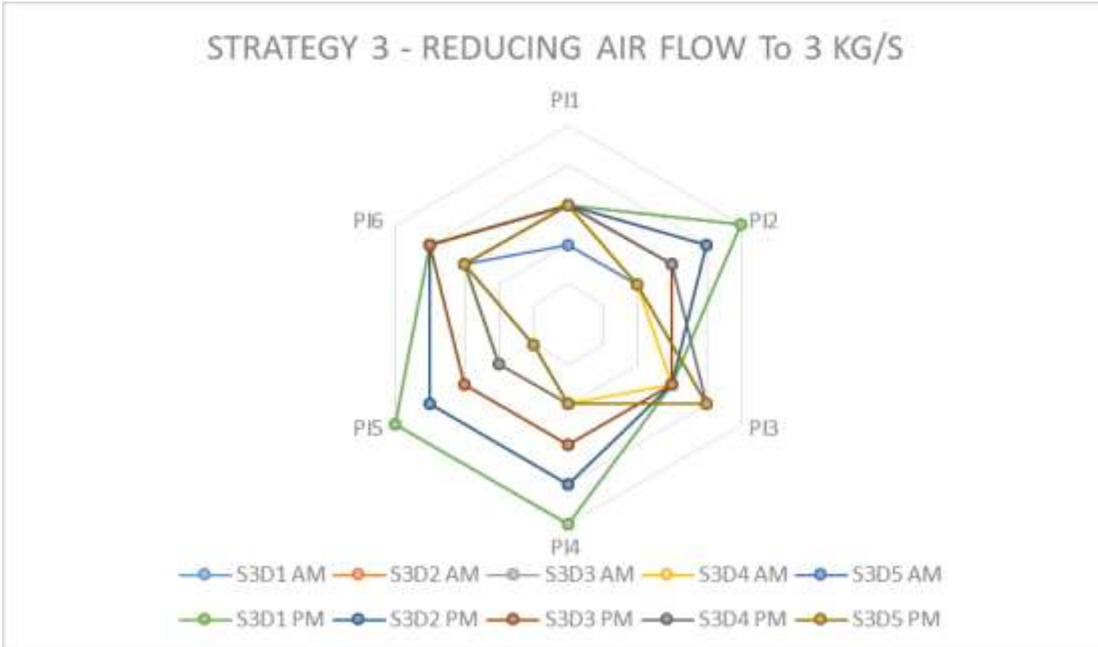



Figure 5.58 Performance comparison of different control scenarios related to air flow reduction to 3 kg/s.

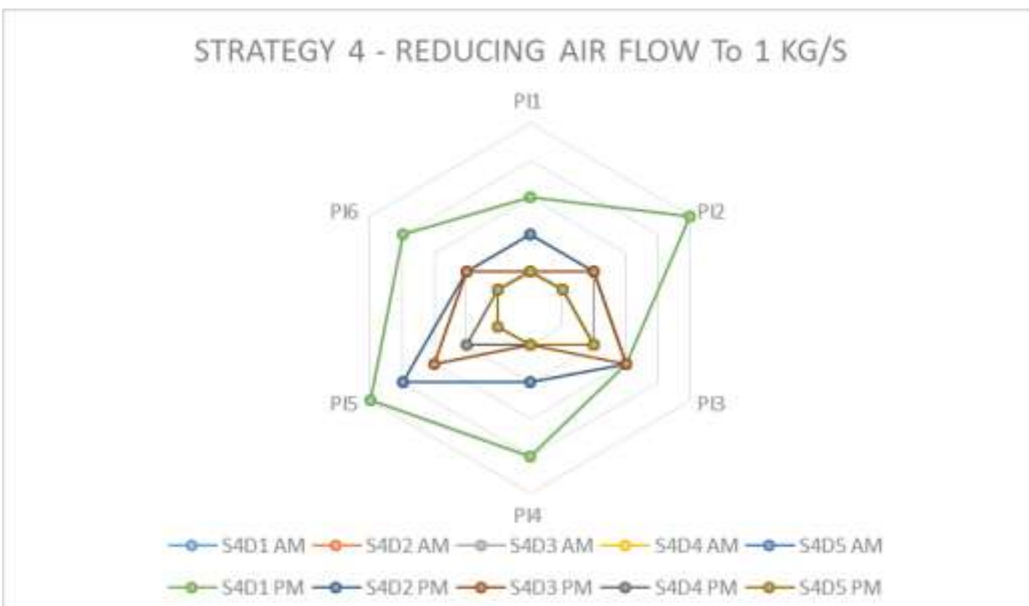



Figure 5.59 Performance comparison of different control scenarios related to air flow reduction to 1 kg/s.


Figure 5.60 Performance comparison of different control scenarios related to powering off the supply fan.

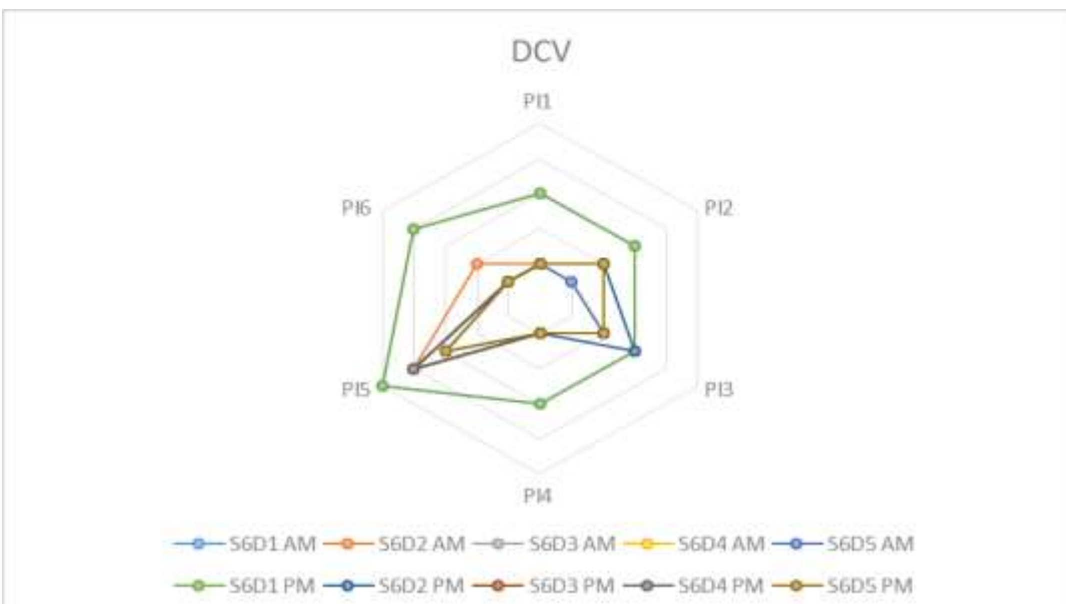



Figure 5.61 Performance comparison of different control scenarios related to powering DCV.

Figure 5.62 depicts results obtained for comparing the best performing strategies from each category of control strategies.

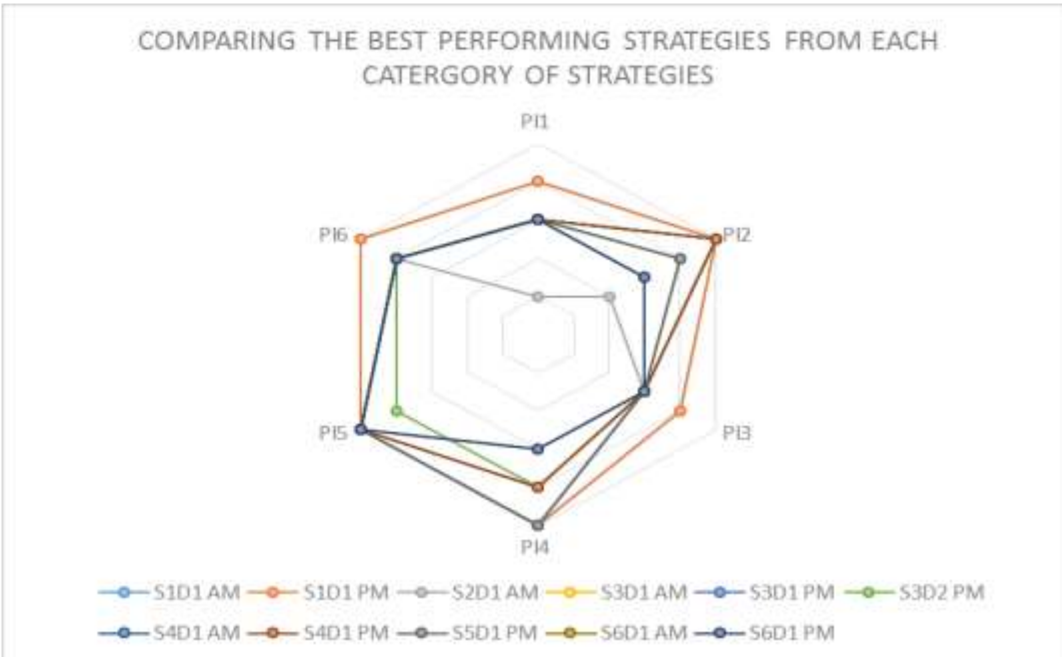



Figure 5.62 Comparing the best performing strategies selected from each category of strategies

## 5.7 Decision Context

To better understand how performance of different control strategies can be compared and assessed using PIs defined, a ‘situation’ is described. This situation defines the decision problem or context, which includes the alternative options, the parties involved, the decision objectives, and preferences (of stakeholders). The decision problem is defined using concepts of decision theory and more specifically the Multi Criteria Decision Analysis (MCDA) approach introduced by Keeney and Raifa (1976). However this decision situation does not represent the full structure of MCDA.

Before getting to the decision context of this study, it should be mentioned that there are different layers of decisions that should be considered during the lifecycle of a building from design to construction and operation. For any new or existing building, one of the main decision problems is allocation of resources in conventional, modern, or futuristic energy efficiency methods. For instance, in case of an existing commercial building, deployment of DR strategies should be evaluated against or in addition to other retrofitting strategies such as replacing windows with more energy efficient ones. Controlling the electric system to reduce energy and demand costs may not be a viable solution for a leaky building with low thermal storage. While better power management of buildings has potential to reduce demand charges, high performance building design and commonly used energy conservation methods have proven to reduce cost of energy. Here, the assumption is that this layer of decision was already finalized and the building is equipped with sensors and instruments to participate in DR or even advanced DR programs such as Auto DR, yet there is no automation at building scale to assist facility managers with 'how to respond' decisions.

Here, the decision context or problem is the selection of an intervening HVAC control strategy at building scale such that it satisfies multiple objectives of different stakeholders as a response to a DR signal in the presence of different alternatives available. A 'preferred', 'best' or 'optimum' outcome is the one that satisfies objectives of most stakeholders e.g., minimizing cost and maximizing comfort. Through this decision situation, we want to answer questions such as: 'how facility managers or automated building energy management systems can use PIs defined to respond to a DR signal to reduce cost of energy and power while maximizing occupant comfort?', 'how these PIs support management and operation of buildings before, during, and after DR events?', and 'how quantitative performance assessment of HVAC control strategies help facility managers and building owners decide what control strategy to select and what is the best time to implement it to arrive at the 'best' outcome?'

The parties involved in a decision problem are the decision maker, the decision analyst, and the stakeholders. In this decision situation, we assume the decision maker and the decision analyst are the same and both are the facility manager; the decision techniques and PIs developed assist them with the decision analysis. The stakeholders involved and their objectives reflect back on the same ones identified earlier under performance scope in Chapter 4. The stakeholders consider here are the building owner and the occupants. There are other entities that are indirect beneficiaries or stakeholders such as the power utility and the society. However, they have no direct influence on the 'decision' and hence not taken into account although they may perceive particular costs or benefits (e.g., a more resilient power system) as a result of the decision taken. In another decision context (beyond the scope of this study) these external stakeholders may well become party in the ultimate decision making.

In the building described in section 5.3.1, the facility manager wants to find an intervening control strategy to respond to DR events scheduled in the first days of July. He/she wants to select a strategy that reduces cost in terms of energy and demand for the building owner while minimizing thermal discomfort for occupants. To find the impact of each control strategy, all PIs should have the same unit to be able to combine their performance and find an overall output. The common unit useful for this decision situation is the dollar amount based on a monetization of all benefits and damages.

### 5.7.1 Monetization of Energy and Demand

Monetization of energy and demand is not a challenge because their economic value (i.e., price) are well established. Although utilities use sort of complex tariffs for electricity rates to charge commercial buildings, a simple charge structure is used here for energy (kWh) and demand (kW). The building selected is located in the state of Washington which has the lowest cost of electricity in the nation after Idaho as shown in Figure 5.63 (EIA, 2016). There is no time of use (TOU) pricing in this location, so a constant rate is assumed to be applied during all hours and all seasons. The average cost of electricity in WA is 7.97 cents/kWh according to EIA. This value is taken as energy charge rate used for the purpose of this study.

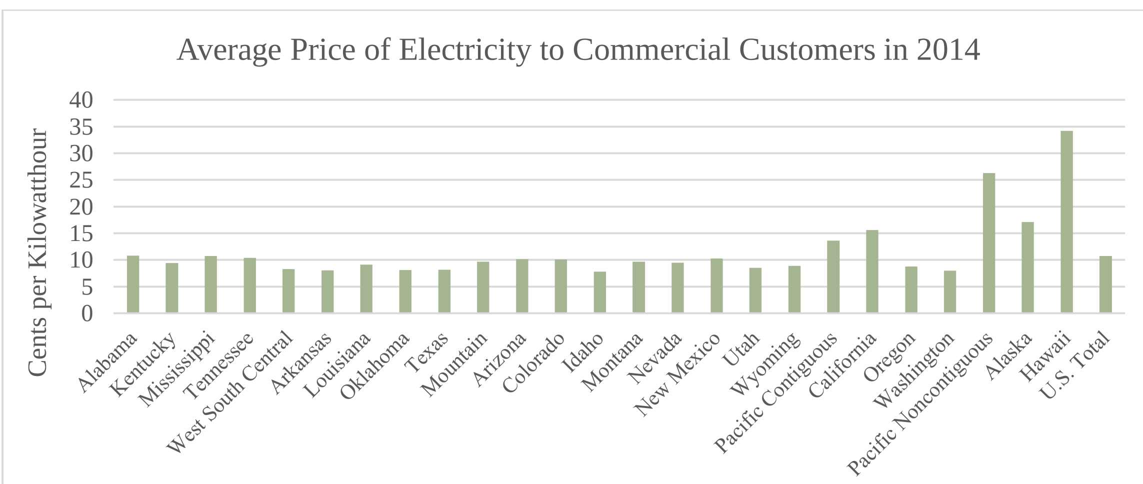



Figure 5.63 Average price of electricity in 2014 (EIA, 2016)

The U.S. Energy Information Administration (EIA) however does not offer data on demand charges ($/kW) nor does it have rates or prices for peak or off-peak periods.

Reviewing the charge structure of some utilities across the U.S. shows that demand charges vary between about \$4/kW to \$18/kW in summer. Since energy rates (\$/kWh) in WA is among the lowest in the U.S. (average is 0.104 and median is 0.097 \$/kWh), it is assumed that demand charges are also below average. Charge rates selected for this study are tabulated in Table 5.8.

Table 5.8 Charge structure used in this decision situation.

| | Rate (\$) |
|---|---|
| Energy (\$/kWh) | 0.0797 ~ 0.08 |
| Demand (\$/kW) | 6.00 |

### 5.7.2 Monetization of Comfort

Unlike energy and demand, comfort does not have a well-established economic value because it is not a commodity traded. However, cost of poor IEQ (which includes thermal comfort) has been estimated in terms of its impact on performance and productivity of occupants in commercial buildings. It is well known that the salaries and benefits of office workers are much higher than the operation and energy cost in office buildings (1% energy costs, 9% rental, and 90% salaries and benefits) (Woods, 1988; Seppänen, 1999). Consequently, the cost of poor IEQ can potentially be significantly higher than building heating and cooling costs (Seppänen 1999). Studies show that improving indoor environment in the US office buildings would result in a direct increase in productivity (0.5% to 5% increase depending on many different building, organizational, demographical and social-cultural aspects). This is estimated to have an economic value of $17 to $26 billion annually[1] (Fisk et al., 2011).

As it was mentioned, air temperature is a common indicator of thermal comfort used in IEQ and productivity research (Lan et al., 2012). There are a number of studies that have objectively quantified the impact of air temperature on occupants' productivity and performance. Wyon (1975) is among those who first attempted to measure the relationship between temperature in summer and in winter (depending on clothing) and performance depending on type of work. The study showed negative impact on performance of office work if temperature was too low or high. Similar observations have been reported by other authors. For instance, Niemelä et al. (2001) found a decrement of 1.8% per °C in productivity when the temperature was raised above 25°C. Federspiel et al. (2002) performed similar study and found no significant correlation between temperature and productivity as long as temperature was maintained in a range defined as 'comfort zone.' However, they reported a 15% decline in productivity as the temperature increased from 24.8 to 26°C. Link and Pepler (1970) measured productivity in a different work environment and reported 8% decrease in workers' performance as the temperature was increased from 23.9 to 32.2 °C. Results obtained from 24 of such studies (3 schoolwork and 21 office work) were evaluated by Seppänen et al. (2006) to create the relationship between temperatures and performance. Figure 5.64 depicts a summary of the results published.

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[1] This estimate includes the impact of different factors including thermal comfort, lighting quality, indoor air pollution, and distractions caused by odors and scents and their effects on productivity.

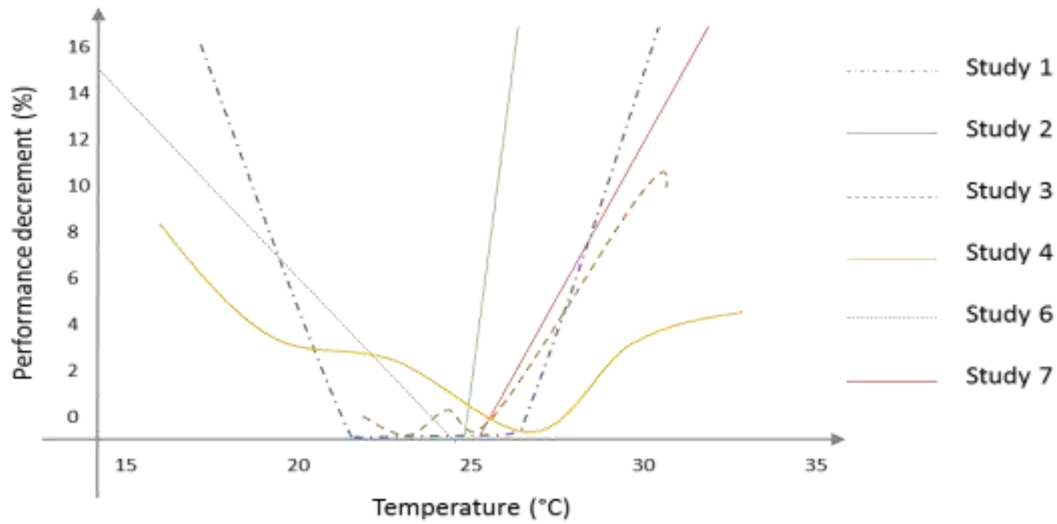


Figure 5.64 Performance Decrements vs. Temperature, Source: Seppänen et al. (2006)

Based on these studies, the dollar value of performance decrement as a result of temperature variation during DR events is estimated. Results are summarized in Table 5.9. The setpoint in the building under study is 21°C. It is assumed that there are 100 employees working in this building with an average salary of $40 per hour.

Table 5.9 Cost of thermal discomfort as a function of air temperature.

| Temperature range | Increase from setpoint | Decrease from setpoint | Performance Decrement (%) | Cost ($/hour/ worker) | Total cost per hour ($/hour) | Total cost per minute ($/min) |
|---|---|---|---|---|---|---|
| 18 – 20°C | - | 1.1 – 3 °C | 5% | $2 | $200 | $3.33 |
| 20 – 21°C | - | 1 °C | 2% | $0.8 | $80 | $1.33 |
| 21 – 25°C | 0 – 3.9 °C | - | 0 | 0 | 0 | 0 |
| 25 – 27°C | 4 – 5.9 °C | - | 2% | $0.8 | $80 | $1.33 |
| 27 – 30°C | 6 – 8.5 °C | - | 5% | $2 | $200 | $3.33 |

### 5.7.3 Overall Performance Assessment

Quantifying all performance indicators in terms of one unit ($) enables applying linear additive models, which are the basis of the MCDA. In additive models, individual values are combined into one overall outcome. An advantage of monetization of performance indicators is that it inherently handles assignment of weights to performance criteria. Otherwise, decision makers and stakeholders involved should determine weights for different performance criteria based on their preferences.

Monetized results and the overall performance are calculated and tabulated in the overall performance To monetize the three power PIs, they are first multiplied by the peak power (because they are unitless) and then monetized using the demand charge of $6. The cost of energy, *PI3*, for each scenario is calculated using energy rate of $0.08/kWh. The cost of occupant thermal comfort is quantified by multiplying costs specified in Table 5.9 by *PI5*, the duration of thermal discomfort, by *PI6*, deviation of air temperature from setpoint. The overall quantity of performance for each scenario can then be used to select the scenario (control strategy + time + duration) resulting in a best possible outcome (i.e., lowest cost).

Table 5.10 Monetized PIs and the overall performance (unranked).

| Scenario | PI1- MAPR ($/day) | PI2 - Disparity ($/day) | PI3 - Energy ($/day) | PI 4 - PPC ($/day) | PI 5 x PI6 Comfort ($/day) | Overall Performance ($/day) |
|---|---|---|---|---|---|---|
| S1D1 AM | 19.8 | 1.9 | 1.2 | 9.4 | 0.0 | 32.3 |
| S1D2 AM | 49.9 | 4.5 | 1.3 | 15.5 | 0.0 | 71.2 |
| S1D3 AM | 60.6 | 5.0 | 1.2 | 17.5 | 0.0 | 84.3 |
| S1D4 AM | 68.2 | 7.0 | 1.2 | 18.7 | 0.0 | 95.2 |
| S1D5 AM | 78.2 | 9.2 | 1.2 | 20.5 | 0.0 | 109.1 |
| S1D1 PM | 18.8 | 1.9 | 1.2 | 9.6 | 0.0 | 31.5 |
| S1D2 PM | 46.3 | 4.3 | 1.2 | 15.0 | 0.0 | 66.9 |
| S1D3 PM | 55.7 | 5.0 | 1.2 | 17.5 | 0.0 | 79.4 |
| S1D4 PM | 54.3 | 5.6 | 1.2 | 17.1 | 0.0 | 78.3 |
| S1D5 PM | 54.6 | 6.2 | 1.2 | 17.3 | 0.0 | 79.3 |
| S2D1 AM | 233.1 | 16.4 | 1.3 | 33.4 | 7.0 | 291.2 |

Table 5.10 Continued

| Scenario | PI1- MAPR ($/day) | PI2 - Disparity ($/day) | PI3 - Energy ($/day) | PI 4 - PPC ($/day) | PI 5 x PI6 Comfort ($/day) | Overall Performance ($/day) |
|---|---|---|---|---|---|---|
| S2D2 AM | 216.7 | 32.8 | 1.4 | 33.3 | 30.1 | 314.2 |
| S2D3 AM | 193.7 | 42.7 | 1.5 | 33.0 | 73.9 | 344.7 |
| S2D5 AM | 157.6 | 46.0 | 1.8 | 32.1 | 178.2 | 415.6 |
| S3D1 AM | 41.1 | 2.7 | 1.3 | 13.3 | 0.0 | 58.3 |
| S3D2 AM | 65.1 | 5.1 | 1.3 | 17.9 | 0.0 | 89.4 |
| S3D3 AM | 79.6 | 7.6 | 1.3 | 20.7 | 0.0 | 109.1 |
| S3D4 AM | 92.3 | 10.3 | 1.3 | 22.8 | 0.0 | 126.6 |
| S3D5 AM | 112.6 | 13.2 | 1.2 | 26.4 | 0.0 | 153.5 |
| S3D1 PM | 42.8 | 2.7 | 1.3 | 13.4 | 0.0 | 60.2 |
| S3D2 PM | 67.7 | 5.2 | 1.3 | 18.1 | 0.0 | 92.2 |
| S3D3 PM | 75.4 | 7.4 | 1.3 | 20.0 | 0.0 | 104.1 |
| S3D4 PM | 82.0 | 8.6 | 1.2 | 21.4 | 0.0 | 113.2 |
| S3D5 PM | 90.9 | 9.9 | 1.2 | 23.4 | 0.0 | 125.4 |
| S4D1 AM | 45.5 | 2.8 | 1.3 | 15.1 | 0.0 | 64.7 |
| S4D2 AM | 133.5 | 12.4 | 1.3 | 31.6 | 0.0 | 178.7 |
| S4D3 AM | 189.2 | 20.7 | 1.3 | 47.5 | 67.2 | 325.9 |
| S4D4 AM | 221.8 | 27.3 | 1.3 | 54.7 | 129.3 | 434.4 |
| S4D1 PM | 40.4 | 2.7 | 1.3 | 14.3 | 0.0 | 58.6 |
| S4D2 PM | 133.3 | 12.3 | 1.3 | 31.5 | 0.0 | 178.5 |
| S4D3 PM | 179.7 | 20.0 | 1.3 | 45.8 | 73.3 | 320.1 |
| S4D4 PM | 209.1 | 26.1 | 1.3 | 52.3 | 138.9 | 427.7 |
| S4D5 PM | 237.7 | 29.7 | 1.3 | 59.4 | 543.5 | 871.6 |
| S5D1 AM | 44.0 | 4.3 | 1.3 | 15.1 | 0.0 | 64.7 |
| S5D2 AM | 183.1 | 17.4 | 1.3 | 37.4 | 36.6 | 275.9 |
| S5D3 AM | 229.8 | 26.3 | 1.3 | 53.4 | 95.5 | 406.3 |
| S5D4 AM | 249.5 | 29.6 | 1.4 | 59.1 | 431.6 | 771.1 |
| S5D5 AM | 266.0 | 32.8 | 1.4 | 65.7 | 663.3 | 1029.2 |
| S5D1 PM | 44.0 | 4.3 | 1.3 | 14.1 | 0.0 | 63.7 |
| S5D2 PM | 187.8 | 17.6 | 1.3 | 37.7 | 40.9 | 285.3 |
| S5D3 PM | 229.0 | 26.2 | 1.3 | 53.1 | 262.1 | 571.7 |
| S5D4 PM | 252.8 | 29.6 | 1.4 | 59.1 | 467.5 | 810.4 |
| S5D5 PM | 262.7 | 32.8 | 1.4 | 65.7 | 711.3 | 1073.8 |
| S6D1 AM | 51.8 | 5.8 | 1.3 | 15.8 | 0.0 | 74.7 |
| S6D2 AM | 185.0 | 17.6 | 1.3 | 37.7 | 37.8 | 279.4 |
| S6D3 AM | 222.2 | 22.5 | 1.3 | 45.0 | 58.3 | 349.4 |
| S6D4 AM | 243.9 | 24.4 | 1.3 | 46.2 | 67.0 | 382.8 |
| S6D5 AM | 262.7 | 26.3 | 1.3 | 49.6 | 77.2 | 417.1 |
| S6D1 PM | 53.2 | 5.8 | 1.3 | 15.8 | 0.0 | 76.1 |
| S6D2 PM | 187.6 | 17.6 | 1.3 | 37.7 | 41.0 | 285.1 |
| S6D3 PM | 213.0 | 21.9 | 1.3 | 43.7 | 63.0 | 342.9 |
| S6D4 PM | 236.2 | 22.3 | 1.3 | 44.7 | 182.8 | 487.4 |
| S6D5 PM | 255.8 | 22.7 | 1.3 | 48.9 | 208.7 | 537.3 |

# 6. CONCLUSIONS

Energy efficiency studies focus on reducing aggregated energy consumption. They traditionally focus on less usage profiles during the day although economic studies in the presence of time of use rates obligate the assessment of the daily usage dynamics. More importantly, consumption studies pay no attention what affects certain interventions in operation can have on the stability of the power system. We argue that the latter requires a set of new measures and modeling/simulation tools that enable a quantification of the power performance of buildings. This will lead to the joint study of energy efficiency and power efficiency of buildings. At the large larger scale this amounts to the quantification of global impact of a building on energy utilization, grid stability and resilience as well as and greenhouse gas emissions.

The objectives of this study were to develop models and methods needed to evaluate building load profiles and instantaneous power consumption of building energy systems to aid DR decisions at building scale. These objectives were addressed by developing coupled thermal-electrical models, defining a set of PIs to measure performance of load and power, and showing applicability of these models and measures through use cases and decision contexts. Quantified outcomes for our case studies show applicability of models and measures developed for decision contexts defined in the modeling chapter (Section 3.6) and performance framework chapter (Section 5.7).

## 6.1 Contribution to the State of Knowledge

"While energy efficiency measures have been widely understood by many audiences including facility managers, building owners, utility program managers, auditors, and policy makers, there are not many documents introducing frameworks or guidelines for measures and strategies to participate in demand response programs. Commercial buildings have been only minor participants in demand response programs" (Motegi et al., 2007). This statement is still valid today despite all efforts and work done in the areas of demand side management and building integration in the power system since 2007.

This thesis introduces a set of measurable performance metrics to evaluate power performance of buildings and their control strategies in the power system. This is an essential part in understanding, assessing, and comparing systems, mechanisms, and strategies in a systematic and scientific way. These measureable PIs are also necessary to construct a framework that can be used to control the negative effects of the integration of buildings in the power system. Furthermore, the set of quantifiable PIs as defined in this thesis enable development of a multi-scale decision making framework to calculate the trade-off between different choices in the presence of multiple objectives. In the case of building-grid interactions, these objectives are maximizing service provided to the grid (e.g., reducing peak) while minimizing energy consumption of buildings.

## 6.2 Contribution to the State of Practice

Peak demand reduction and DR are key parts of energy policies in different states. However, customers and facility managers have limited knowledge of how to operate their buildings to reduce their electricity costs (Quantum and Summit Blue 2004). Lack of knowledge about how to develop and implement control strategies to respond to DR programs is certainly a challenge and limitation. But, in addition to that, the lack of automation in evaluating control strategies to respond to a DR signal is another restriction.

Most Dashboards available today are energy dashboards, which provide facility managers, building owners and building occupants with real-time energy data. Although some of these dashboards provide facility managers with tips or recommendations on how to save energy, the main goal of existing dashboards is to display building performance data. Berkeley Campus Energy Portal is an example of such an energy dashboard (http://berkeley.openbms.org/map). Existing Pacific Northwest Dashboard, DSOM (Decision Support for Operations and Maintenance) also provides an energy dashboard for real-time monitoring (http://pnl.gov/dsom). There are a growing number of DR dashboards. EnergyConnect's *GridConnect* platform from Johnsons Control provides DR dashboard to end-users (Johnson Controls, 2012). *GridConnect* is designed to give customers information to choose the DR deal that best fits the requirements of their facility. There are also DR dashboards from larger aggregators, such a*s EnerNoc*, *Comverge*, and *Constellation Energy's VirtuWatt platform*. These dashboards aim to engage commercial customers with the spot market and help them manage their load.

The advantage of these DR dashboards over energy dashboards is that they provide more information to the user, however, they still lack quantifiable measures to assess performance of one strategy or scenario against another one. The set of quantifiable PIs defined can be used in energy and power dashboards to evaluate performance of different strategies in detail. An example of such dashboard is illustrated in Figure 6.1.


Figure 6.1 Example of an energy and power management dashboard with detailed analysis using quantifiable PIs.

In addition to the application of performance quantification for building operation and facility management, measurable PIs can also be used during the design phase. Design of DR control strategies would ideally take place during the new construction commissioning phase and be incorporated into the commissioning process according to Kiliccote et al. (2006a). Measurable PIs can be used during this phase to evaluate performance of different HVAC systems and control strategies to select one that best suit preferences of building owner and occupants.

## 6.3 Future work

Although models and methods presented in this work can be effectively used for applications mentioned, there are further enhancements that can be made. In terms of modeling, the thermal-electrical models developed in Chapter 3 are loosely coupled models. These models can well handle electrical variations within thermal cycles calculated by thermal models. However, we need tightly coupled electrical and thermal models to capture the direct impact of electrical changes on thermal characteristics of buildings (e.g., temperature). These tightly coupled models should be defined as a function of both electrical and thermal inputs e.g., temperature and voltage.

In terms of quantifiable PIs developed, more building and system types can be used to define a wider range of normative scenarios. PIs should be calculated for all these different buildings with different system types to find the relationship between each PI and control specifications defined. For instance, by finding the performance of different systems in terms of the length of uncomfortable minutes for different durations [minutes] of DR when the setpoint is increased by 2, 3, or 4ºC, we can find equation of the curve that can robustly quantify the PI for any other given system.

In terms of performance evaluation method used, the ranking method can be enhanced using decision analysis methods. These methods can support both manual and automated DSM decisions. Hence, this work will be continued by integrating methods such as multi-attribute utility theory with building energy and power management systems and dashboards. This method will enable weighing all of the attributes (i.e., measurable quantity) and scaling them by the level of importance to the stakeholder (or decision maker). PI's defined can serve as attributes in this theory. The major addition to apply utility theory is the explicit quantification of uncertainty (in the model) and risk attitude (for the decision maker). For this reason an attribute (or PI) is now regarded as an outcome that is uncertain, as the result of uncertain parameters in the model. We need to (1) obtain a probability distribution of each PI for each alternative, and (2) assign levels or ranks for decision makers' preferences.

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